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Retail Credit Risk Management

Edited by Mario Anolli, Elena Beccalli and Tommaso Giordani

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Retail Credit Risk Management

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Renzo Traversini is Business Development Director at the Italian branch of SAS Institute srl, leading a team of professionals dedicated to tracking market trends, understanding customer requirements, and designing software solutions to support key business processes in customer organizations. His areas of interest are mainly related to designing and implementing information systems for risk management (especially in banking), with particular emphasis on internal rating systems, portfolio credit risk management, and also market risk systems, operational risk systems, and integrated risk modeling.

Part I
Regulatory Framework

1
Introduction

Mario Anolli and Elena Beccalli

1.1 Why retail credit risk management?

Why the need for a book on retail credit risk management? The first, and probably the most important, reason is the perceived usefulness of investigating risk management not only in terms of the general theory on modeling and methods, but also to gauge its managerial implications and its interconnections with other bank operations and with the firm's organizational structure. Risk management is not simply a tool; it is a managerial action. In fact, risk management materializes in a series of concrete daily actions, and it cannot be limited to risk modeling and regulatory compliance (Basel II and III above all). The insight here is to overcome the merely quantitative risk management approach with two prior aims: on the one hand, to consider risk management as a continuous forecasting action not limited to single events; and on the other hand, to prevail over the common misinterpretation that risk management is solely a necessitated, and to a certain extent annoying, consequence of the regulatory risk-control discipline (Basel II and III).

The second reason is the adoption of a distinctive focus on retail credit, characterized by a huge number of operations and customers – private individuals and small to medium size enterprises (SMEs) – where a single loan has only a negligible impact on the relevant economic dimensions. Although not affected by the complexities of corporate risk management, retail risk management introduces the problem of numerical complexity due to the huge amount of data to be processed. The ability to elaborate, manage, and store a very large amount of data becomes essential and highlights structural synergies with other firm operations, such as IT systems.

The third and last reason is that the 2007 financial crisis has had strong implications for retail risk management, both in the short term and in the long term. In the short term, there is an effect on the cost of portfolio management and the cost of collection. Specifically, in terms of the customers' creditworthiness, evaluation, and monitoring, a need exists to overcome the highly streamlined evaluation process and the excessive reliance on credit bureau scores without further insights into the current assets and liabilities of the applicants and their income perspectives. As for the long term, clearly the need exists to better capture the link between the macroenvironmental factors and the risk of the credit portfolio, which then affects impairment and capital absorption. The issue is complex due to the lack, to date, of models and tools able to incorporate macroenvironmental factors and certain credit factors that had been undervalued in the previous growth cycle (such as affordability of financial liabilities, over-indebtedness risk, and the resilience of the individual and the household). In this sense, banks now need to develop models that take into account unemployment rates, market interest rates, inflation rates, affordability, over-indebtedness risk, and resilience. Last but not least, due to the crisis the risk management department has to effectively communicate to the senior management the additional risk derived from the crisis in order to add it into the planning actions for capital and commercial pricing. Commercial pricing is not a static input connected with a short-term strategy; it should instead incorporate a line of defense against adverse scenarios mainly connected to the liquidity gap. According to this perspective, risk management should actively participate in the decisions on price setting by providing a "professional" forward-looking perspective not only to minimize impairment and capital absorption but also to guarantee the sustainability of medium-term revenues.

1.2 The book

This book introduces the fundamentals of retail credit risk management, provides a broad and applied investigation of the related theory on modeling and methods, and explores the interconnections of risk management with other firm operations and industry regulations. The distinctive focus on retail customers and the continued implications of the financial crisis for risk management is the main benefit of this book. Furthermore, the involvement of academics, regulators, and professionals from major global banks and consulting firms provides a global focus with the right balance between theory and application.

The book is structured in four parts: Part I provides a comprehensive and updated discussion of the regulatory framework; Part II investigates the first phase of the risk management process (risk taking) by looking at the measurement, pricing, and management of retail credit; Part III is devoted to the second phase of the risk management process, that is, the measurement and management of portfolio credit risk; and Part IV deals with the operational implications of credit risk management for other functions.

1.2.1 Part I: the regulatory framework

Chapter 2, by Damiano Guadalupi, critically discusses the evolution of the Basel Accord. The author argues that the success of the international capital standards in preventing banking distress has been mixed. Basel I's regulatory rules were arbitraged due to their risk insensitivity; this gave rise to Basel II with its greater focus on risk calibration. However, Basel II collapsed under the 2007 financial crisis when the concern on the procyclicality of the revised Accord became evident. Amendments have since been applied through Basel III. According to Guadalupi, however, even before the new capital buffers under Basel III come into force, if the market perceives that the capital ratio that includes the capital conservation buffer (7%) will never be breached, then dynamic buffers will no longer exist and ratings will again become the only instrument to achieve the two different objectives. These objectives measure the actual creditworthiness of borrowers and mitigate procyclicality. The likely result might be that both of them will remain out of reach.

1.2.2 Part II: risk taking: measurement, pricing, and management

Chapter 3, by Corrado Giannasca and Tommaso Giordani, focuses on the phases within the development of an acceptance model for private individuals. The authors start with the decision to develop the new model, and then progress to its full implementation. Throughout the chapter, the authors assess the pros and cons of credit risk modeling for operational processes, policy definitions, business goal setting, and organizational change. Further, Giannasca and Giordani argue that the 2007 financial crisis has resulted in more scrutiny of the credit risk management tools that have been developed and used in the last decades. The main lessons learned, in their view, are related to an increased awareness of data quality and of the wider scope needed to control the sustainability of customer obligations, and an increased awareness of the role of the macrovariables that become mandatory to evaluate their impact

on customers and portfolio performances. Impacts on economic measures that result from stressed economic conditions represent the new risk management's challenge for long-term business sustainability.

Chapter 4, by Emanuele Giovannini, focuses on the phases within the development of an internal rating model for SMEs. The author discusses the data sources used in the process, the indicators to compute, the variables to include in the shortlist, the correlation model between dependent and independent variables, the caliber function adopted to convert the score rating into the probability of default (PD), and the number of rating classes. Giovannini emphasizes that along common guidelines suggested by the banking authority, each bank develops its own model. He contextualizes the discussion by providing examples related to Italian banks.

Chapter 5, by Elisa Alghisi Manganello and Valentina Leucari, focuses on loss given default (LGD), the critical parameter in risk modeling, by discussing its definition, relevance, and application. In addition to being crucial for compliance requirements, LGD has several implications for the daily management of the credit portfolio. In fact, there are several issues directly related to a business prospective: the recovery cycle's efficiency and duration, the commission scheme's efficiency, the pricing definition within a debt sale, the links between sustainable recovery flows, and the impacts on LGD levels and therefore the coverage included within the risk planning. By taking into account both the product-specific characteristics as well as the underlying recovery process, the authors critically discuss the various families of models that can be suitable for LGD estimation: conditional means models calculating an average LGD within certain segments, regression models estimating LGD as a linear function of relevant selected explanatory variables, and chain-ladder models that aim to predict future recovery curves starting from observed ones.

Chapter 6, by Antonio Arfé and Paolo Gianturco, deals with the internal validation of the rating systems that is part of the general framework for rating system controls. The authors highlight that according to both local and international regulatory requirements, validation activities should not exhaustively use empirical validation methods and tests, but should also be concerned with several aspects of the rating system, and assess the overall functioning of the rating system along different dimensions, including the method, the IT system and data quality, and the processes and governance. Following the Basel Committee on Banking Supervision's guidelines, to comply with the normative framework "banks must have a robust system in place to validate the accuracy and

consistency of rating systems, processes, and the estimation of all relevant risk components. A bank must demonstrate to its supervisor that the internal validation process enables it to assess the performance of internal rating and risk estimation systems consistently and meaningfully." Their chapter focuses on the rating system's internal validation approaches for the retail segment. The authors take into account the possible organizational structures for the implementation of the activities, and the main tools and processes. They provide a specific focus on the quantitative aspects in terms of the analysis of the models, the methodological backgrounds of the statistical tests, the interpretation of possible outcomes, and the actions to be taken in accordance with the results.

Chapter 7, by Mario Anolli, offers a framework for investigation into the risk-adjusted performance of decisions relating to retail credit. Taking risk into account in an efficient manner is highly important in retail credit risk management because of the large number of small decisions that could, in the absence of a correct decision-making framework, lead to the undesired bundling of huge risks. The risk-adjusted performance measures are also important to the capital allocation process and to the overall enhancement of the long-term profitability of the bank.

1.2.3 Part III: portfolio credit risk: measurement and management

Chapter 8, by Lorenzo Bocchi and Tiziano Bellini, provides an analysis of the different credit risk models for portfolios, and highlights how these models can be used for both regulatory and managerial purposes. To compute internal capital requirements, the regulatory framework imposes Gordy's (2003) model of the Advanced Internal Rating Based (AIRB) approach. However, the assumptions of the IRB are not always in line with the managerial issues of banks, so the credit risk models for portfolios are developed with different incentives and purposes; they are primarily for portfolio management, risk-based pricing, capital allocation, and stress testing. A case study complements the chapter, illustrating how to use credit risk models in credit risk management.

Chapter 9, by Tiziano Bellini and Lorenzo Bocchi, emphasizes the role played by credit portfolio models in assessing the capital adequacy of banks. Stress test analyses are required under Basel II in order to use the IRB approach to compute the credit capital requirement. Stress testing comprises several techniques used to assess the vulnerability of a portfolio to major changes in the economic environment and to exceptional but plausible events. The authors show how to implement stress

tests in practice, and present a case study on stress testing where the identification of the scenario can be based either on an hypothetical setting (such as that for the European Banking Authority, 2011) or on an historical setting. In addition, they investigate the role of credit risk models for portfolios in the capital planning process by emphasizing the key role of risk-adjusted performance measures to implement effective capital allocation.

Chapter 10, by Tommaso Giordani and Corrado Giannasca, provides an overview of the main ingredients of credit portfolio management. The authors illustrate these ingredients in a comprehensive framework (rather than as single elements) ultimately finalized to minimize both impairment (credit losses) and capital consumption and to measure the risk-adjusted profit for homogeneous clients or individual applicants. The authors identify three managerial areas in the portfolio management framework. First, they identify the portfolio's vulnerability to the economic cycle, collection efficiency, strategy effectiveness, and the potential impacts from the new model's development (application, impairment, and capital) and the calibration of the existing models. Second, new business planning looks at the client segment that is considered strategic for the bank, the pricing strategy for the client, and a consistent acceptance strategy. Third, they identify the timely monitoring of the divergences from the key objectives embedded in the plans. Moreover, Giordani and Giannasca explore what should be the optimal organizational structure and communication approach for efficient management of the stakeholders.

1.2.4 Part IV: operational implications

Chapter 11, by Renzo Traversini and Anselmo Marmonti, provides an analysis of the IT systems for credit risk management. These systems, part of the wider IT infrastructure, support key activities such as risk taking, risk management, risk mitigation, and risk pricing. The authors emphasize that all banks have already set up the overall credit management process along Basel II's guidelines, and that banks are now focusing their attention on the evolution of the system by aiming to increase control over the system overall, and over the performance of their IT systems specifically, ensuring that the resultant measures are available to the business process in good time. Banks also aim to increase the performance of the models for a more precise valuation of the risk. Specifically, large banks aim to improve the quality of the data involved in the process of credit risk management.

Chapter 12, by Francesco Merlin, emphasizes that prior to the recent financial crisis, numerous banks revamped their credit underwriting, monitoring, and collection processes with a focus on speed, costs, efficiency, and customer satisfaction. The one thing they forgot to consider properly was effectiveness, or risk management, and many subsequently got into trouble (meaning a higher rate of nonperforming loans, huge credit losses, and provisions). Several banks are now reevaluating their retail credit processes (along with credit risk models) with a renewed emphasis on risk management and lower losses. By focusing jointly on efficiency and effectiveness, banks can learn important lessons from the crisis and adapt appropriately to the new dynamics of credit demand and supply. This chapter outlines the key structural trends and best practices that are reshaping banks' retail credit risk management in underwriting, monitoring, and collection processes.

Part II

Risk Taking: Measurement, Pricing, and Management

2
The Ever-evolving Basel Accord

Damiano Guadalupi

2.1 Introduction

Walter Bagehot in his *Lombard Street*, published in 1873, wrote, "A well-run bank needs no capital. No amount of capital will rescue a badly run bank". Unfortunately, regulators cannot easily require banks to be "well-run" in Bagehot's sense, so banks are required to hold capital as a backstop. Capital is not a bad substitute for perfect judgment, and at least it can be defined and measured (Davies, 2011). But how much capital is necessary to support the overall risk taken by a bank?

The determination of a bank's optimal capital level is an issue on which academics, bankers and regulators have different views. The solution that regulators provide consists of the regulatory capital requirements proposed by the Basel Committee on banking supervision (BCBS) in 1988, and that the supervisory authorities of over 150 countries have implemented.

The Basel Capital Accord, originally intended specifically for large, internationally active banks, has in practice served as the basis for the risk-based capital adequacy standards for most banking organizations worldwide. In fact, although the Basel Accord applies to the international banks in member countries, many countries require all their banks to adhere to the Basel rules. For example, in the EU the Basel Accord has been introduced via directives and is mandatory for all European financial institutions.

Over the 24 years since the Basel Accord was adopted, the framework has been repeatedly refined to take into account changes in banking and the banking system. In particular, capital requirements originally set in 1996 to cover credit risk only were extended to market risks and

in 2004 to operational risks. Furthermore, in 2004 the Basel Committee completely revised the 1988 approach to credit risk.

This chapter is intended to provide readers with an overview of the basic mechanism of the Basel Capital Accord that plays such a key role in defining the management policies of banks. In fact, since its introduction, banks committed to improving their risk assessment practices with the aim of estimating the amount of capital absorbed by their activities must consider the constraints represented by the mandatory capital requirements of the Basel Accord. Therefore, the regulatory capital requirements have also had a relevant impact on the development strategy adopted by banks over the last 20 years, and have instigated major changes in management systems and organizational processes.

2.2 The 1988 Capital Accord

The 1988 Accord, now familiarly known as Basel I, assessed capital mainly in relation to credit risk, and addressed other risks only implicitly, effectively loading all regulatory capital requirements onto measures of credit risk. Basel I required banks to have regulatory capital amounting to at least 8 percent of their total risk-weighted assets:

$$\text{Capital Ratio}_{\textit{Basel}\,1} = \frac{\text{Regulatory Capital}}{\text{Risk-Weighted Assets}} \geq 8\%$$

The capital ratio is calculated using the definition of regulatory capital and risk-weighted assets (BCBS, 1988).

2.2.1 Regulatory capital

According to Basel I, the key elements of capital are equity capital and disclosed reserves. These key elements are the only components common to all countries' banking systems, they are wholly visible in the published accounts, and they are the basis on which most market judgments of capital adequacy are made. Notwithstanding this emphasis, member countries of the BCBS have suggested that there are a number of other elements of a bank's capital base that should be included within the system of measurement.

The BCBS concluded that for supervisory purposes capital should be defined in two tiers in a way that will require at least 50 percent of a bank's capital base to consist of a core element mainly comprised of equity capital[1] and disclosed reserves[2] (Tier 1). In the case of consolidated accounts, Tier 1 will also include minority interests in the equity

of subsidiaries that are not wholly owned. This basic definition of capital excludes revaluation reserves and cumulative preference shares.

In 1998, the BCBS, noting that certain banks had issued a range of innovative capital instruments with the aim of generating Tier 1 regulatory capital, decided to limit acceptance of these instruments for inclusion in Tier 1 capital.[3] Such instruments were subject to stringent conditions (such as being permanent; being junior to depositors, general creditors and subordinated debt of the bank; able to absorb losses within the bank on a going-concern basis; callable at the initiative of the issuer only after a minimum of five years with supervisory approval; and under the condition that it would be replaced with capital of the same or better quality) and limited to a maximum of 15 percent of Tier 1 capital. Any extra could be counted toward Tier 2 capital. Thus, innovative capital instruments are also known as Lower Tier 1, as opposed to Upper Tier 1 for the other components.

The other elements of capital (supplementary capital) are admitted into Tier 2 but are limited to 100 percent of Tier 1 and are subject to certain conditions. Each of these elements might or might not be included by national authorities at their discretion in the light of their national accounting and supervisory regulations.

In 1996, Tier 3 capital was introduced only as coverage for market risk. In fact, at the discretion of their national authority, banks can also use a third tier of capital that consists of short-term subordinated debt for the sole purpose of meeting a proportion of the capital requirements for market risks (BCBS, 1996).

The components of the regulatory capital are summarized in Table 2.1.

2.2.2 Risk-weighted assets

The denominator of the capital ratio is the risk-weighted assets, which are a measure of the amount of a bank's assets (and off-balance-sheet exposures) adjusted for risk. The underlying rationale is that banks' assets have different risk profiles and that riskier assets require higher amounts of capital. The Basel Committee designed a system of risk weights (0 percent, 20 percent, 50 percent, and 100 percent) to measure the riskiness of banks' assets. Assets are assigned to one of those four risk weights on the basis of their features (debtor type, debtor's country of residence, and asset type). Thus, assets considered to be riskier are assigned to a higher weight.

Before being assigned to the appropriate risk-weighted categories, off-balance sheet exposures are converted to loan equivalent exposures on the basis of rules that predict the likelihood of actual credit exposure.

Table 2.1 Components of regulatory capital in the Basel Accord

Component			Limits and restrictions
TIER 1	*Upper* Tier 1	Paid-up share capital / common stock	At least 4 percent of RWA
		Disclosed reserves (e.g., retained earnings and share premium reserves)	
	Lower Tier 1	Innovative capital instruments	No more than 15 percent of T1
TIER 2	*Upper* Tier 2	Undisclosed reserves	No more than 100 percent of T1
		Revaluation reserves	
		General provisions / general loan- loss reserves	
		Hybrid (debt / equity) capital instruments	
	Lower Tier 2	Subordinated term debt	No more than 50 percent of T1
TIER 3	Short-term subordinated debt covering market risks		No more than 250 percent of T1 for market risk
Deductions	Goodwill		Deducted from T1
	Investments in nonconsolidated banks and financial institutions		Deducted 50 percent from T1 and 50 percent from T2 capital

Basel I's fundamental objectives were to promote the soundness and stability of the international banking system and to provide a level playing field for international competition among banks.

In particular, Basel I played a major role in reversing the gradual decrease in the capitalization of the most advanced banking systems: the capital to total assets ratio gradually declined from about 15–20 percent at the beginning of the 20th century to less than 10 percent in the 1970s. After 1988, the average capital ratio of major banks in developed countries steadily increased. This increase reflected not only the direct effect of Basel I, but also improved market discipline, because the introduction of consistent standards for banks worked to increase transparency and

Table 2.2 Risk weights in the standard approach

Risk weights	On-balance sheet assets	
Credit conversion factor		Off-balance sheet exposures
0 percent	Cash and cash equivalents Claims on central banks and central governments of OECD countries Government bonds issued by OECD countries	Commitments unconditionally revocable at any time
20 percent	Claims on multilateral development banks Claims on banks in OECD countries Claims on public entities in OECD countries Claims on banks in non-OECD countries with a maturity of less than 1 year	Commitments with an original maturity of up to 1 year Self-liquidating, short-term commitments associated with business transactions (e.g. documentary credits)
50 percent	Loans secured by mortgage on residential property	Commitments with an original maturity of more than 1 year Commitments associated with non-financial transactions (e.g., performance bonds) Documentary credits granted and confirmed Note issuance facilities (NIFs) and revolving underwriting facilities (RUFs) Other lending commitments (unutilized credit lines) with an original maturity of over 1 year

Table 2.2 (*cont.*)

Risk weights	On-balance sheet assets	
Credit conversion factor		Off-balance sheet exposures
100 percent	Claims on the private sector Equity investments in private companies Claims on non-OECD banks and central governments Plant and other fixed assets	Direct credit substitutes (e.g., irrevocable stand-by letters of credit). Asset sales with recourse, in which the bank bears the credit risk

improved the market's ability to exert pressure. Moreover, Basel I has effectively contributed to reducing competitive inequality among banks in different countries.[4]

2.2.3 Basel I limits

Notwithstanding its merits, inherent in Basel I are some flaws that affected the effectiveness of the overall capital framework as time went by. The most relevant limitations are the following:

Recognition of a single source of risk

Basel I focuses on credit risk only. Other relevant sources of risks, namely interest rate risk, market risk, and operational risk, are ignored. Only in 1996 did the Committees amend the Accord to extend capital requirements to market risk.

Limited differentiation of risk

Basel I is based on only a limited differentiation of risk that uses a broad category of exposure with an 8 percent charge for all exposures except OECD governments,[5] OECD interbanks, under one-year non-OECD interbanks, and residential mortgages. The requirements mainly reflect the type of borrower and not the riskiness of the loan (except for the OECD/non-OECD distinction and the recognition of some types of financial collateral) and therefore do not change if the creditworthiness of borrowers deteriorates. Thus, all private borrowers are rated as equally risky, and companies with different ratings are required to meet the same

capital requirements. By the same token, all loans to non-OECD countries are rated as riskier than loans to OECD countries, regardless of their respective ratings.[6]

Inadequate consideration of the relation between borrower risk and loan maturity

Despite the fact that loans with a longer maturity (life horizon) are riskier, Basel I only considers to a very limited extent the link between maturity and credit risk. In fact, only some short-term exposures (off-balance sheet exposures and interbank loans) are required to face lower capital requirements.

Neglect of loan portfolio diversification benefits

Basel I does not reward banks that reduce their systematic risk, because no recognition is given for risk diversification of a bank's loan portfolio. If portfolios with a high number of well diversified loans require the same level of capital as portfolios heavily concentrated on just a few borrowers, industries, or geographies, then banks do not have any incentive to diversify credit risk.

Moreover, the limitations of Basel I widens the gap between regulatory capital and the measures of capital at risk that banks estimate according to internal models. Banks are encouraged to engage in regulatory arbitrage to exploit such differences. The typical transaction is a securitization of assets that have a high risk weighting. Banks can either cherrypick safe assets to sell, or securitize on terms such that default risk is not transferred but merely taken off the balance sheet. Regulatory arbitrage can also transform how assets are treated (for example, securities with a high credit rating can have a lower risk weighting than the assets backing them). This means that the capital requirement for the banking system as a whole can fall even though the same risks are being absorbed, leading to an increase in systemic risk.

2.3 The new Capital Accord (Basel II)

2.3.1 General features

In response to the criticism of Basel I, the BCBS worked to amend and complete the original framework. In 1996, it issued an amendment to extend the regulatory capital requirements to market risks that allowed banks to use their internal models for regulatory purposes, subject to the approval of the supervisory authority. In 1999, the BCBS began an extensive review of credit risk requirements and addressed the issue

of operational risk. A number of changes were made that culminated in the 2001 proposal (BCBS, 2001). Over 250 comments from banks, together with the Committee's three impact studies, resulted in substantial changes to the original document. A final consultative document was published in April 2003, and the final version of the new Capital Accord (Basel II) was released in June 2004 (BCBS, 2004).

Basel I's fundamental objectives were to ensure the solvency of the banking system and the consistency of internationally competitive conditions. Basel II set forth a new objective, by promoting capital requirements more sensitive to the underlying risk of the assets, thus narrowing the gap between regulatory capital and the internal capital that banks measure. To this aim, capital requirements were extended to a broader range of risk (credit; market; and, for the first time ever, operational risks), and the capital requirements' calculation rules were improved to better reflect the risk of the underlying positions. Moreover, Basel II emphasizes the roles of both the supervisory process aimed at reviewing and assessing supervised banks' overall capital adequacy and of the market to discipline banks' behavior.

Thus, Basel II consists of three mutually reinforcing pillars: Pillar 1, that sets new, more precise, rules for calculating minimum capital requirements for credit, market, and operational risks; Pillar 2, that provides guidelines aimed at reinforcing the internal governance and risk management of banks and at developing an intensive interaction between supervisors and banks; and Pillar 3, that establishes core disclosure by banks in order to improve market discipline.

In practice, Basel II affirms that minimum capital levels, though calculated more accurately, are not enough to fulfill supervisory goals: in an increasingly complex environment, capital adequacy cannot be assessed without taking into consideration the functioning and the reliability of the firm's risk management system. Equally important is the disciplinary function that market participants – investors, rating agencies and financial analysts – can perform.

With respect to Basel I, Pillar 1 of Basel II was not a novelty: banks are required to maintain a minimum capital level to support risk taking; the minimum level of the ratio of capital to risk-weighted assets is kept at 8 percent; different weightings are assigned to various types of assets with different risk profiles. What changed were the risk categories that banks must consider, and the rules for calculating capital requirements.

The new capital requirements are not limited to credit risks. In Basel II, a new capital requirement is introduced to operational risks, whereas capital charges on market risk are still calculated according to the guidelines

set in 1996. The market risk capital rules were recently amended to tackle the problems that emerged during the financial crisis.

One of the most relevant innovations of Basel II is the system of alternative rules for calculating the minimum capital requirements. In particular, with respect to Basel I, rules for calculating the denominator of the capital ratio have been profoundly modified, while the minimum level that banks must hold (8 percent) and the numerator definition have not.

$$\text{Capital Ratio}_{Basel\ 2} = \frac{\text{Regulatory Capital}}{\text{RWA}_{Credit\ risk} + 12{,}5 * \text{K}_{Market\ risk} + 12{,}5 * \text{K}_{Operational\ risk}} \geq 8\% \tag{2.1}$$

The denominator is the sum of the assets weighted by risk: assets weighted by credit risk are directly computed; but for market and operational risks, the capital requirement is multiplied by 12.5 (the reciprocal of 8 percent) to ensure consistency in calculating the overall denominator.

For each risk type, banks can choose among different methods that range from a simplified approach to one or more internal methods that are increasingly complex but are also more accurate. Basel II offers economic incentives for banks to adopt more sophisticated approaches and hence to improve their risk and capital management practices. Table 2.3 illustrates the possible approaches.

As for credit risk, in contrast to Basel I, loans extended to similar borrowers are subject to different regulatory capital requirements depending on their specific riskiness. In fact, Basel II permits banks a choice between two broad methods for calculating their capital requirements for credit risk. One alternative, the standardized approach, is to measure credit risk in a standardized manner supported by external credit assessments. The other alternative, the internal ratings-based (IRB) approach, is subject to

Table 2.3 Pillar 1 approaches for the calculation of minimum capital requirements

Credit risk	Counterparty risk	Market risk	Operational risk
Standardized	Current exposure method	Standardized	Basic Indicator Approach
IRB Foundation	Standardized	Internal models	Standardized
IRB Advanced	Internal model (EPE)		Internal model (AMA)

the explicit approval of the bank's supervisor and allows banks to use their internal rating systems for credit risk.

Under the IRB approach, two broad methods are available: foundation and advanced. Under the foundation method, as a general rule, banks provide their own estimates of the probability of default (PD) for borrowers and rely on supervisory estimates for other risk components, the levels of losses, and exposures at the time of default, namely the loss given at default (LGD) and the Exposure at Default (EAD). Under the advanced method, the banks provide more of their own estimates of the PD, LGD, and EAD, and their own calculation of the maturity of the loans (M), subject to meeting minimum standards.

Rules introduced in 1996 for calculating capital requirements for market risks have not significantly changed with reference to calculation methods: banks can choose between a standardized system and an internal model for risk measurement. To be accepted for regulatory purposes, the internal models have to conform to some minimum requirements and are subject to supervisory approval.

The definition of operational risk is "the risk of loss resulting from inadequate or failed internal processes, people and systems, or from external events". Basel II presents three methods, in a continuum of increasing sophistication and risk sensitivity, for calculating the capital charges from operational risk: the basic indicator approach; the standardized approach; and the Advanced Measurement Approach (AMA).

Banks that use the basic indicator approach must hold capital for operational risk equal to the average over the previous three years of a fixed percentage (15 percent) of positive annual gross income.

In the standardized approach, bank activities are divided into eight business lines. Within each business line, gross income is a broad indicator that serves as a proxy for the scale of business operations and thus the likely scale of operational risk exposure within each of these business lines. The capital charge for each business line is calculated by multiplying gross income by a factor assigned to that business line. Each factor serves as a proxy for the industry-wide relation between the operational risk-loss experience for a given business line and the aggregate level of gross income for that business line. The total capital charge is calculated as the three-year average of the simple sum of the regulatory capital charges across each of the business lines in each year. Under the AMA approach, the regulatory capital requirement equals the risk measure generated by the bank's internal risk measurement system. Use of the AMA is subject to supervisory approval.

Pillar 2 requires banks to adopt a process for assessing their overall capital adequacy in relation to their risk profile and a strategy for maintaining their capital levels. Also the risks not adequately covered under Pillar 1 (such as credit concentration and correlation) and the risks not in Pillar 1 at all (such as interest rate risk on the banking book) have to be considered in the Pillar 2 framework. Moreover, banks must also carefully monitor the effect played by some bank-external factors (such as the economic cycle), even developing suitable stress-testing methods and tools.

Against this backdrop, supervisory authorities expect banks to operate with an amount of capital in excess of the minimum requirements, and they can request banks to hold a higher amount of capital than the minimum requirement. To this end, supervisory authorities perform an overall review of the risk and capital management processes carried out by the individual banks that aim at evaluating processes, techniques, and strategies to calculate and maintain adequate capital levels. The supervisory review process enables authorities to promptly intervene in order to avoid capital falling below the minimum requirement.

Pillar 2 focuses on this supervisory review process. In fact, the banks' internal risk measurement systems are recognized as more accurate and more closely tailored to the specific risk profile of each individual bank than the universal Pillar 1 system. However, the assessment of the full reliability of such banks' internal processes requires an intensive interaction between the supervisory authorities and the banks.

The principle underlying Pillar 3 is that market discipline can play an effective role in assessing banks' financial conditions and thus complement the minimum capital requirements (Pillar 1) and the supervisory review process (Pillar 2) if market participants have reliable, detailed and prompt information on risks and capital. To this end, Basel II encourages market discipline by defining a set of disclosure requirements that allows market participants to assess key pieces of information on capital, risk exposures, risk assessment processes, and hence the capital adequacy of each individual institution. Banks that adopt more advanced approaches to calculate capital requirements are required to comply with stricter disclosure criteria.

The standardized approaches were to be adopted by the G-10 countries' banks by the end of 2006, and the advanced approaches were to take effect at the end of 2007. During the first year of implementation, banks and national regulators were expected to run parallel calculations that computed capital requirements based on Basel I and Basel II.

2.3.2 Credit risk: the standardized approach

The Basel II standardized approach is the new standard method available to banks to calculate their minimum credit risk capital requirement. As mentioned before, Basel I applies one of four fixed risk weights, from zero to 100 percent, to each exposure depending on its type. The minimum capital requirement is set at 8 percent of the relevant fixed risk-weighted exposures.

The standardized approach is similar in principle to the existing rules, as banks must continue to calculate the minimum credit risk capital requirement at 8 percent of the total of their risk-weighted exposures depending on the exposure class. The key differences are the greater risk sensitivity of the approach and the use made of external credit ratings; under the new rules, banks must assign their credit exposures to one of a wider range of exposure classes and apply more risk-sensitive weightings to them. These range from zero to 150 percent depending on the credit quality of the exposure.

The standardized approach increases the risk sensitivity of the capital framework by recognizing that different counterparties within the same loan category present very different risks to the financial institution's lender. Thus, instead of placing all commercial loans in the 100 percent risk-weight basket, the standardized approach takes into account the credit assessment of recognized external credit assessment institutions (ECAI) – such as credit ratings agencies – to determine the risk weight for each exposure.

The Basel Committee recognizes that there were certain difficulties in placing reliance on such assessments. There also are concerns about the incentive and the consequential effects of a more extensive use of external assessments in Basel II. For these reasons, the Basel Committee proposes that national supervisors should not allow banks to put assets into preferential risk-weighting categories in a mechanical fashion, based on external assessments. Rather, banks should do so only where they themselves and their supervisors are satisfied with the quality of the assessment source and method. Therefore, banks must adopt a consistent approach in using a particular assessment mechanism, and should not cherrypick assessment methods. Weighting applied to the main assets classes are the following.

Claims on sovereigns and their central banks

Basel I applies different risk weights to claims on sovereigns and their central banks that depend on whether the claim is on a member of the OECD.

On the contrary, the new system permits the risk weights applied to such claims to be benchmarked to the assessment results of eligible ECAIs. Under Basel II, the zero-weighted category is limited to sovereigns with the highest credit quality (those, for example, with a minimum rating of AA- under the method used by Standard & Poor's); claims on countries rated A+ to A- are eligible for a 20 percent risk weight; claims on countries rated BBB+ to BBB- are eligible for a 50 percent risk weight; claims on countries rated BB+ to B- are risk-weighted at 100 percent, as are those on countries without a rating; and claims on countries rated below B- are weighted at 150 percent. The assessments used should generally be in respect to the sovereign's long-term foreign currency obligations.

A modified treatment is available for banks' exposures to their own sovereign (or central bank) denominated in domestic currency and funded in that currency. National supervisors of such banks can decide to provide a lower risk weight for such exposures where they judge it appropriate. Where this discretion is exercised, other supervisory authorities can allow their banks to apply a risk weighting similar to that of the domestic banks.

Claims on banks

Basel I states that all claims on banks incorporated in OECD countries and short-term claims (that is, up to one year) on banks incorporated in non-OECD countries should be risk-weighted at 20 percent. It also requires that long-term claims on banks incorporated in non-OECD countries should be risk-weighted at 100 percent.

Such an approach is replaced with an approach based on external credit assessments. In particular, there are two options for claims on banks. National supervisors apply one option to all banks in their jurisdiction.

Under the first option, all banks incorporated in a given country are assigned a risk weight that is one category less favorable than that assigned to claims on the sovereign of that country. For example, if a claim on the bank's sovereign is weighted at 20 percent, then a claim on that bank is weighted at 50 percent. However, for claims on banks in countries with sovereigns rated BB+ to B- and on banks in unrated countries, the risk weight is capped at 100 percent. The exception to this cap is for claims on banks of the lowest-rated countries (for example, below B- in Standard & Poor's method) where the risk weight on the bank is capped at 150 percent.[7]

The second option is to use ratings assigned directly to banks by an ECAI. Most claims on banks, including unrated banks, receive a 50 percent weighting. However, claims of very high quality (for example, AAA

to AA- in Standard & Poor's method) receive a 20 percent weight, claims on banks with a rating of BB+ to B- a 100 percent weighting, and claims on banks with a rating below B- a 150 percent risk weighting. Claims on banks of a short original maturity, of less than three months (other than the lowest-rated), receive a weighting that is one category more favorable than the usual risk weight on the bank's claims. For example, if a claim on a bank is weighted at 50 percent, a short-dated claim on that bank is weighted at 20 percent. The floor for all claims on banks is 20 percent, and no claim on a bank can receive a risk weight less than that applied to claims on its sovereign.

Claims on corporates

An evident shortcoming of Basel I was that inadequate recognition was given to the differing credit quality of claims on corporates. In Basel II, the standard weighting for claims on corporates remains at 100 percent, but a weighting of 20 percent is given to claims on corporates of a very high quality (for example, a minimum rating of AA- in Standard & Poor's method), and a weighting of 150 percent is given to claims on corporates that are of very low quality (rating below B).

Claims included in the regulatory retail portfolios

In Basel I, claims on retail customers were not considered autonomously, except for loans secured by residential property. In Basel II, claims that qualify under four specific criteria are considered as retail claims for regulatory capital purposes and are included in a regulatory retail portfolio:

The *orientation criterion*, where the exposure is to an individual person, or persons, or to a small business.

The *product criterion*, where the exposure takes the form of any of the revolving credits such as lines of credit, personal term loans, leases, and small business facilities and commitments. Securities, whether listed or not, are specifically excluded from this category. Mortgage loans are excluded to the extent that they qualify for treatment as claims secured by residential property.

The *granularity criterion*, where the supervisor must be satisfied that the regulatory retail portfolio is sufficiently diversified to a degree that reduces the risks in the portfolio, warranting the 75 percent risk weight. One way of achieving this diversification might be to set a numerical limit that no aggregate exposure to one counterpart can exceed 0.2 percent of the overall regulatory retail portfolio.

The *low value of individual exposures* is where the maximum aggregated retail exposure to one counterpart cannot exceed an absolute threshold of 1 million. Exposures included in such a portfolio are risk-weighted at 75 percent.

Claims secured by residential property

Lending that is fully secured by mortgages on residential property occupied by the borrower, or that is rented, is risk-weighted at 35 percent (50 percent in Basel I).

Past due loans

The unsecured portion of any loan (other than a qualifying residential mortgage loan) that is past due for more than 90 days, net of specific provisions (including partial write-offs), is risk-weighted at 150 percent. When specific provisions are not less than 20 percent of the outstanding amount of the loan, the latter is risk-weighted at 100 percent. When specific provisions are not less than 50 percent of the outstanding amount of the loan, the supervisor can reduce the risk weight to 50 percent.

Higher-risk categories

Claims on sovereigns, banks and corporates with very low ratings are risk-weighted at 150 percent. National supervisors can decide to apply a 150 percent or higher risk weight that reflects the higher risks associated with some other assets, such as venture capital and private equity investments.

Assets securitization

The Basel Committee was concerned with some banks' use of structured financing or asset securitization to avoid maintaining capital commensurate with their actual risk exposures. In fact, in Basel I the same economic risk can result in substantially different capital requirements depending on the type of transaction a bank uses. Basel II's standardized approach sets a specific weighting system for securitization transactions that requires higher capital requirements for banks investing in junior or equity tranches and is aimed at avoiding a bank being able, through such techniques, to achieve an overall risk-based capital ratio that is nominally high but might obfuscate capital weakness in relation to the actual economic risks inherent in the bank's portfolio. Table 2.4 summarizes the main risk weightings in the standardized approach.

The risk weightings in Table 2.4 apply to unsecured exposures. Recognizing that banks have developed a number of techniques to mitigate the credit risks to which they are exposed, the Basel Committee adopted

Table 2.4 Risk weightings in the standardized approach

	AAA AA−	A+ A−	BBB+ BBB−	BB+ BB−	B+ B−	Below B−	Unrated	Past due*
Sovereigns	0	20	50	100	100	150	100	150
Banks								
Option 1 (Country of incorporation)	20	50	100	100	100	150	100	150
Option 2	20	50	50	100	100	150	50	150
Option 2 (residual life < 3 months)	20	20	20	50	50	150	20	150
Corporates	20	50	100	100	150	150	100	150
Retail	75	75	75	75	75	75	75	150
Residential real estate mortgages	35	35	35	35	35	35	35	100

*When specific provisions are not less than 20 percent of the outstanding amount of the loan, past due is risk-weighted at 100 percent; when they are not less than 50 percent, the supervisor can reduce the risk weight to 50 percent.

a revised approach to credit risk mitigation (CRM) that allows a wider range of credit risk mitigants to be recognized for regulatory capital purposes than had been permitted under Basel I. Thus, banks are allowed to reduce capital requirements by obtaining collaterals that meet the requirements for legal certainty as described in Basel II.[8]

In addition to the general requirements for legal certainty, the legal mechanism by which collateral is pledged or transferred must ensure that the bank has the right to liquidate or take legal possession of it, in a timely manner, in the event of the default, insolvency, or bankruptcy of the counterparty (and, where applicable, of the custodian holding the collateral). Moreover, banks must have clear and robust procedures for the timely liquidation of collateral to ensure that any legal conditions required for declaring the default of the counterparty and liquidating the collateral are observed, and that collateral can be liquidated promptly.

Banks can opt for either the "simple" approach that, as in Basel I, substitutes the risk weighting of the collateral for the risk weighting of the counterparty for the collateralized portion of the exposure (generally subject to a 20 percent floor), or for the "comprehensive" approach that allows a fuller offset of the collateral against exposures by effectively reducing the exposure amount by the value ascribed to the collateral. It

must be calculated by applying a haircut that reflects the risk that the market value of the financial instruments provided as collateral by the obligor might decrease in the course of the loan term. Banks have two ways of calculating the haircuts: standard supervisory haircuts that use parameters set by the Basel Committee, or own-estimate haircuts that use banks' own internal estimates of market price volatility. Supervisors can allow banks to use own-estimate haircuts only when they have met certain qualitative and quantitative criteria.

2.3.3 Credit risk: the Internal Rating Based (IRB) approach

The IRB approach to regulatory capital is one of the main innovations of Basel II and is aimed at ensuring that, for an individual bank, regulatory capital requirements better reflect that bank's particular risk profile.

The IRB approach is based on a bank's own quantitative and qualitative assessments of its credit risk (internal *rating*). More sophisticated banks use internal ratings to summarize the risk of individual credit exposures and to incorporate into various banking functions, including operational applications (such as determining loan approval requirements) and risk management and analysis (comprising analysis of pricing and profitability as well as internal capital allocation).

Internal ratings incorporate supplementary customer information that is usually out of the reach of an ECAI, such as detailed monitoring of the customers' accounts and greater knowledge of any guarantees or collateral. Internal ratings also cover a much broader range of borrowers and provide assessments of the credit quality of individuals and SMEs through credit scoring and the assessment of larger nonrated borrowers through detailed analysis. Thus, in offering a parallel alternative to the standardized approach based on internal ratings, banks are encouraged to further develop and enhance internal credit risk management and measurement techniques rather than place an unduly broad reliance on credit assessments conducted by ECAIs.

The term "rating system" comprises all the methods, processes, controls, and data collection and IT systems that support the assessment of credit risk, the assignment of internal risk ratings, and the quantification of default and loss estimates.

The greater use of risk parameters from internal rating systems as inputs to capital calculations is one of the key elements of the new framework and confirms the choice made in 1996 with reference to market risks. Such an approach can secure two fundamental objectives consistent with those which support the wider review of Basel I: the first is *additional risk*

sensitivity, in that a capital requirement based on internal ratings can prove to be more sensitive to the drivers of credit risk and economic loss in a bank's portfolio; the second is *incentive compatibility*, in that an appropriately structured IRB approach can provide a framework that encourages banks to continue to improve their internal risk management practices.

Internal rating systems must be approved by the national supervisors: the supervisory assessment of the compliance with the regulatory minimum requirements is aimed at ensuring that the bank is able to provide prudential inputs to the capital calculations. In taking this step, the Basel Committee does not intend to dictate the form or operational detail of banks' risk management policies and practices, but to put forward a detailed set of minimum requirements designed to ensure the integrity of these internal risk assessments. Each national supervisor is required to develop a set of review procedures for ensuring that banks' systems and controls are adequate to serve as the basis for the capital calculations.

Banks that have received supervisory approval to use the IRB approach can rely on their own internal estimates of risk components in determining the capital requirement for a given exposure. The risk components include the measures of the probability of default (PD), loss given default (LGD), the exposure at default (EAD), and effective maturity (M). The risk components serve as inputs to the risk-weight functions that have been developed for separate asset classes (for example, there is one risk-weight function for corporate exposures and another for qualifying revolving retail exposures). In fact, the IRB approach allows banks to use their own internal risk components in the derivation of regulatory capital requirements, but it stops short of permitting banks to calculate their capital requirements on the basis of their own (or vendor) portfolio credit risk models.

In some cases, banks might be required to use a supervisory value as opposed to an internal estimate for one or more of the risk components. Depending on the reliability of their models and on the quality of the underlying data and information, banks can be allowed to adopt two different methods: a *foundation* method in which banks input their own assessment of the PD but refer to standardized supervisory values for the other risk components (LGD, EAD, M); and an *advanced* method that allows banks to use their own internal estimates for all the aforesaid risk components.

Therefore, the main components of the IRB approach are the following: *asset classes*, that consist of a classification of exposures by broad exposure type, *risk components,* that can be banks' internal estimates or

standardized regulatory parameters that banks use for calculating capital requirements, *risk-weight functions,* that provide risk weights (and hence capital requirements) for given sets of risk components, and *minimum requirements* that a bank must meet in order to be eligible for adopting the IRB approach for supervisory purposes.

Asset classes

Empirical evidence shows that there can be significant differences across business lines or portfolios in the key risk factors and rating criteria on the one hand, and the historical loss characteristics or relations on the other. These differences translate into key differences in the distribution of credit loss events for the different portfolios, and thus different relations between risk characteristics and unexpected loss or required capital.

The above motivates the requirement that under the IRB approach, banks must categorize banking-book exposures into broad classes of assets with different underlying risk characteristics. The classes of assets are *corporate*, *sovereign*, *bank*, *retail*, and *equity*. Within the corporate asset class, five subclasses of specialized lending are identified, and within the retail asset class, three subclasses. Banks are required to apply the appropriate treatment to each exposure for the purposes of deriving their minimum capital requirement. Banks must demonstrate to supervisors that their method for assigning exposures to different classes is appropriate and consistent over time.

Given the specific target of this book, the retail asset class is worth focusing on, because Basel II addresses it specifically. In fact, while the broad conceptual framework and quantitative approach developed for the other asset classes are also appropriate for retail exposures, the differences in asset characteristics and risk management practices specific to retail require a certain adjustment to the general IRB framework. This section highlights these key issues and elaborates on the framework for retail exposures.

The Basel Committee's analysis highlights a diverse range of practice in the approach to rating retail exposures. One of the most significant differences between corporate and retail portfolios occurs in the methods used to differentiate risk.

For corporate exposures, the dominant practice (and the basis of the corporate IRB approach) is to use a structured rating system that assigns a specific rating to each borrower, based on a combination of objective and subjective criteria. The rating is oriented to the risk of borrower default, and changes in asset quality are expected to result in changes to this

rating. This type of rating allows the rating system to remain relatively constant, with shifting portfolio quality reflected in a changing distribution of ratings. Because they can remain relatively fixed over time, these internal ratings are often linked to a schedule of average PDs.

For retail loans, the use of a fixed borrower rating scale and the assignment of individual borrower ratings is much less common. Rather, banks commonly divide the portfolio into "segments" (or "pools") made up of exposures with similar risk characteristics, or that are thought to behave in a consistent manner based on underwriting or other criteria. Banks then assess risk and quantify loss characteristics (PD, LGD, EL, and EAD) at the segment (or pool) level rather than at the individual exposure level. The expectation is that the exposures in a given segment will exhibit homogeneous default characteristics, and that loss performance will follow predictable patterns over the forecast periods.

Another key distinction between banks' practices for corporate and retail portfolios relates to the use of score-driven processes. In marked contrast to corporate lending, where expert judgment plays a significant role for banks that use statistical rating models, one common characteristic of retail portfolios at most banks is the fundamental reliance on scoring, or associated automated practices, for managing the approval, monitoring, control and collections functions. Development and maintenance of these scoring approaches are fundamental prerequisites for effective and dynamic risk control in these markets.

The work undertaken by the Basel Committee highlights that the definition of retail can differ markedly across banks and countries. In some countries, the category mainly comprises high-volume and low-value consumer lending. In others, the definition also includes some business relations. Given that the Committee's proposal consists of an IRB approach for retail portfolios distinct from that for the corporate portfolio – with respect to inputs, the risk weightings, and minimum requirements – an objective definition of the retail asset class is required to ensure consistency in the application of the regulatory IRB framework.

This definition is based on a number of criteria that seek to capture homogeneous portfolios comprising a large number of small, low-value loans with either a consumer or business focus, and where the incremental risk of any single exposure is small. As such, an exposure is categorized as a retail exposure if it meets all of the following criteria: nature of borrower or low value of individual exposures, and large number of exposures.

Nature of borrower or low value of individual exposures: Exposures to individuals such as revolving credits and lines of credit, as well as personal

term loans and leases, are generally eligible for retail treatment regardless of exposure size, although supervisors might wish to establish exposure thresholds to distinguish between retail and corporate exposures. Residential mortgage loans are eligible for retail treatment regardless of exposure size so long as the credit is extended to an individual who is an owner or occupier of the property. Loans extended to small businesses and managed as retail exposures are eligible for retail treatment provided the total exposure of the banking group to a small business borrower (on a consolidated basis where applicable) is less than 1 million. Small business loans extended through or guaranteed by an individual are subject to the same exposure threshold.

Large number of exposures: The exposure must be one of a large pool of exposures that are managed by the bank on a pooled basis. Small business exposures below 1 million can be treated as retail exposures if the bank treats such exposures in its internal risk management systems consistently over time and in the same manner as other retail exposures. This treatment requires that such an exposure be originated in a similar manner to other retail exposures. Furthermore, it must not be managed individually in a way comparable to corporate exposures, but rather as part of a portfolio segment or pool of exposures with similar risk characteristics for purposes of risk assessment and quantification. However, this does not preclude retail exposures from being treated individually at some stages of the risk management process. The fact that an exposure is rated individually does not by itself deny the eligibility as a retail exposure.

Risk components

The capital charge for exposures within each of the asset classes presented above depends on a set of risk components: PD, LGD, EAD, and M. The risk components serve to measure the level of possible future losses on each exposure.

The PD is the key parameter under the IRB framework, as it must be provided by banks in both the standardized and the advanced approaches. As for the other risk components, a distinction has to be made between banks authorized to use the foundation or the advanced approach. In particular, the former uses standard parameters set by regulators.

In a framework based on a separate and explicit assessment of the PD, LGD, and EAD of an exposure, it is important to highlight that the Basel Committee adopted a reference definition of default in order to promote consistency.

In fact in the default-oriented IRB framework, data sources used to estimate PDs and other loss characteristics necessarily incorporate a view of what represents an event of default. Similarly, accounting procedures and other internal administrative processes in the credit risk area are linked to specific interpretations of the meaning of default. Discussions with banks and surveys indicated that in practice definitions of default used in the credit risk measurement context varied across banks, across accounting regimes, and across external databases of historical borrower performance. These differences could affect the comparability of capital requirements on otherwise identical portfolios by possibly placing some banks at a competitive disadvantage solely due to the default definition associated with the data source(s) they use. In an extreme case, such differences could provide opportunities for banks to manage their working definitions and estimation procedures toward inappropriately low capital requirements.

In general, the range of different default definitions can be described as occurring early in the process of a borrower's deterioration, or alternatively as coming late in that process: an example of an early definition of default is the violation of a loan covenant (for example, a minimum operating cash flow); an example of late definition is filing for protection from a bankruptcy court. Because many borrowers experience some initial problems yet recover fully later, a tabulation of historical defaults based on early definition tends to show a higher number of defaults, whereas when based on late definition it tends to show a lower number of defaults, each with a larger associated loss.

With this backdrop, the Basel Committee adopted a regulatory reference definition under which a default occurs when one or more certain events take place. The elements of the reference definition come from within the range of default definitions in use at a number of banks with well managed risk management systems, and comprise both objective and subjective events.

A default is considered to have occurred with regard to a particular obligor when either or both of the following two events have taken place: the bank considers that the obligor is unlikely to pay its credit obligations to the banking group in full without recourse by the bank to actions such as realizing security; the obligor is past due more than 90 days on any material credit obligation to the banking group (in the case of retail exposures, national supervisors can substitute a figure of up to 180 days for different products appropriate to local conditions). The PD is the likelihood that a client of a bank will be unable to meet its debt obligations over a one-year time horizon. The PD used for regulatory

purposes is the one-year PD associated with the internal borrower's grade (or rating class) to which each single exposure (or pool of exposures in the retail segment) is assigned.

Each estimate of the PD must represent a conservative view of a long-run average PD for the grade in question, and thus must be grounded on historical experience and empirical evidence. Preparation of the estimates, and the risk management processes and rating assignments that lie behind them, must reflect full compliance with supervisory minimum requirements (including internal use and disclosure requirements associated with the estimates) to qualify for IRB recognition.

The LGD is the percentage of a credit exposure that a bank expects to lose if the borrower defaults. The LGD is influenced by many factors, such as the facility's seniority and the presence of collateral, the borrower's industry characteristics, and the peculiarities of the bank managing the recovery process, or external factors such as macroeconomic conditions.

Under the foundation approach, a 45 percent LGD is prescribed for senior claims on corporations, sovereigns, and banks not secured by recognized collaterals. Such value is increased to 75 percent for subordinated claims on the aforesaid asset classes. The LGD can be reduced for loans assisted by adequate collaterals. In addition to the eligible financial collateral recognized in the standardized approach, under the foundation approach some other forms of collateral, known as eligible IRB collateral, are also recognized; these include receivables and specified commercial and residential real estate where they meet the minimum requirements set out by Basel II. Therefore, if collateral represented by financial instruments is provided, the LGD can be reduced to zero depending on the value of the eligible financial instruments after the application of the haircuts (see Table 2.5). If other eligible IRB collaterals are provided, LGD can be reduced to 40 percent (35 percent in case of trade receivables and real estate).

Under the advanced approach, banks determine the LGD to be applied to each exposure on the basis of robust analysis and data relating to similar exposures and borrowers. Thus, a bank using internal LGD estimates for capital purposes might be able to differentiate LGD values on the basis of a wider set of transaction characteristics (for example, product type or a wider range of collateral types) as well as borrower characteristics. As with the PD estimates, the LGD values must represent long-term default weighted averages, although banks are free to use more conservative estimates. Banks are required to calculate the economic LGD that can be very different from the accounting one. Economic LGD means that all costs (direct as well as indirect) incurred with recoveries must be

Table 2.5 Correlation values(ρ)

Asset classes / subclasses	Asset correlation (ρ)
Corporate, Sovereigns and Banks	12% – 24%, depending on the PDs
Corporate / Small and Medium-sized entities (SMEs)	12% – 24%, depending on the PDs, with a size adjustment to be applied for annual sales between 5m and 50m)
Corporate / High volatility commercial real estate	12% – 30%, depending on the PDs
Retail / Residential real estate exposures	15%
Retail / Qualifying Revolving Retail exposures	4%
Retail / Other retail exposures	3% – 16%, depending on the PDs

included in the loss estimate, and that the discounting effects have to be integrated. Banks wishing to use their own estimates of the LGD need to demonstrate to their supervisor that they can meet additional minimum requirements pertinent to the integrity and reliability of these estimates.

The EAD is a bank's expected gross exposure for a loan on the borrower's default. For fixed exposures, such as bullet or term loans, the EAD is the amount outstanding at the time of the capital calculation (plus accrued but unpaid interest and fees). For variable exposures, such as lines of credit, the EAD is the current amount outstanding plus an estimate of additional drawdowns and accrued but unpaid interest and fees up to the time of default. For amortizing loans, it is possible that the amount outstanding at default might be less than the amount outstanding at the time of the capital calculation if the payment received is more than the net accrued but without unpaid interest and fees. However, under Basel II, the EAD cannot be less than the amount of the outstanding balance at the time of the capital calculation.

Under the foundation approach, the EAD is equal to 75 percent of the commitments and credit lines that are not immediately and unconditionally revocable. The 75 percent figure works in the same way as a credit conversion factor in the standardized approach. Where a facility comprises both a drawn amount and an undrawn amount, the EAD is calculated as (100 percent of) the drawn amount plus 75 percent of the undrawn balance. The 75 percent credit conversion factor is an estimate of the extent to which the part of a committed line that is currently undrawn is drawn down prior to default. Empirical analysis suggests that the commitment factor falls as credit quality declines; while top

quality borrowers tend to have low average utilization rates, experience suggests that they draw heavily on undrawn lines if they encounter difficulties. Therefore, a commitment factor of 75 percent is appropriate to capture this dynamic. In contrast, while lower quality borrowers tend to have higher utilization rates, banks have in place mechanisms such as more frequent review of the account or covenants to restrict further drawdown that serve to reduce the possibility of further drawings. For these borrowers, 75 percent might be on the high side, but given that these borrowers tend to draw quite heavily (and have few unused lines), the degree of model fit in imposing a single commitment factor is not inappropriately undermined.

Under the advanced approach, banks are free to use their own estimates of the EAD on facilities with uncertain drawdowns, subject to meeting the supervisory requirements. As with the LGD, these requirements are not prescriptive in terms of the factors that banks must consider in the assignment of exposures to EAD categories (such as type of facility). Instead, the onus is on the bank to demonstrate that the criteria it uses are reasonable and can be supported by the evidence.

Finally, M is 2.5 years for all credits under the foundation approach. Banks authorized to adopt the advanced approach have to estimate M taking into account the impact of any intermediate payments during the loan life. The result must be truncated to five years, if necessary, while maturities of less than one year are permitted in only a few specific cases.

Risk-weight functions

Risk components are converted into risk weights, and hence regulatory capital requirements, by means of risk-weight functions specified by the Basel Committee (Gordy, 2003). As explained earlier, the IRB approach allows banks to use their own internal risk components when calculating regulatory capital requirements, but it does not permit banks to calculate them on the basis of their portfolio credit risk models. In fact, the Basel Committee finds that the development state of credit risk models could not ensure an acceptable degree of comparability across institutions and that data constraints would prevent validation of key model parameters and assumptions.

Therefore, the Committee uses its own specific credit model to derive the regulatory risk-weight functions. For its purposes, the Committee makes reference to the Vasicek (2002) one-factor model, which is an analytical default-mode model formulation, as the basis for the capital requirement calculation. The model specification is subject to an important restriction in order to fit supervisory needs: capital requirements are

portfolio invariant that means the capital required for any given loan depends only on its own characteristics and not on those of the portfolio it is added to.

Portfolio invariance is an essential property in order to make the IRB framework applicable to a wide range of countries and institutions. Nevertheless, portfolio invariance makes recognition of institution-specific diversification effects within the framework difficult: diversification effects depend on how well a new loan fits into an existing portfolio. As a result, the IRB approach is calibrated for well diversified banks. When a bank deviates from this ideal, it is expected to address this under Pillar 2 of the framework. If a bank fails to address the deviation, supervisors have to take action under the supervisory review process.

Two conditions are necessary and sufficient to guarantee portfolio invariance: the portfolio must be asymptotically fine-grained in the sense that no single exposure in the portfolio can account for more than an arbitrarily small share of total portfolio exposure; and there must be only a single systematic risk factor.

Only the so-called asymptotic single risk factor (ASRF) models are portfolio invariant. ASRF models are derived from common credit portfolio models by the law of large numbers. In fact, when a portfolio consists of a large number of relatively small exposures, idiosyncratic risks associated with individual exposures tend to cancel one another out, and only systematic risks that affect many exposures have a material effect on portfolio losses. In the ASRF model, all the systematic risks that affect all borrowers to a certain degree, such as industry or regional risks, are modeled with only one (the single) systematic risk factor.

Given the ASRF framework, it is possible to estimate the sum of the expected and unexpected losses associated with each credit exposure. This estimation is accomplished by calculating the conditional expected loss for an exposure that is given an appropriately conservative value of the single systematic risk factor. Under the particular implementation of the ASRF model adopted for Basel II, the conditional expected loss for an exposure is expressed as a product of a PD that describes the likelihood that an obligor will default, and a LGD parameter that describes the loss rate on the exposure in the event of default.

The implementation of the ASRF model makes use of average (or unconditional) PDs that reflect expected default rates under normal business conditions. These unconditional PDs are estimated by banks. To calculate the conditional expected loss, the unconditional PDs are transformed into conditional PDs using a supervisory mapping function. The conditional PDs reflect default rates given an appropriately conservative

value of the systematic risk factor. The same value of the systematic risk factor is used for all instruments in the portfolio.

The mapping function used to calculate conditional PDs from unconditional PDs is derived from an adaptation of Merton's (1974) single asset model to credit portfolios. According to Merton's model, borrowers default if they cannot completely meet their obligations at a fixed assessment horizon, because the value of their assets is lower than the due amount. Merton models the value of the assets of a borrower as a variable whose value can change over time. He describes the change in value of the borrower's assets with a normally distributed random variable.

The percentage change that will occur next year in the value of assets of the i-th borrower can be expressed as a linear combination of two variables: X, which is correlated to the macroeconomic cycle, and ε_i, which depends solely on the idiosyncratic risk of the borrower.

$$Z_i = w \cdot X + \sqrt{1-w^2} \cdot \varepsilon_i \tag{2.2}$$

Depending on the weights used in the formula, a borrower can be more or less exposed to the cycle: as w increases, all borrowers tend to be more and more correlated with one other, whereas a decrease in w means that the idiosyncratic characteristics prevail and that the individual borrowers are more independent.

Vasicek (2002) shows that under certain conditions, Merton's model can naturally be extended to a specific ASRF credit portfolio model. On the basis of Merton's and Vasicek's contributions, the Basel Committee decided to adopt the assumptions of a normal distribution for the systematic and idiosyncratic risk factors. It implies that Z_i is also standard-normally distributed. For each pair of i and j borrowers, the correlation between asset value changes is given by:

$$\begin{aligned}\rho_{i,j} \equiv E\left[Z_i Z_j\right] = w^2 E\left[X^2\right] + w \cdot \sqrt{1-w^2} E\left[X\varepsilon_i\right] + w \cdot \sqrt{1-w^2} E\left[X\varepsilon_j\right] \\ + \left(1-w^2\right) E\left[\varepsilon_i \varepsilon_j\right] = w^2\end{aligned} \tag{2.3}$$

In line with Merton's model, borrower i becomes insolvent if and only $Z_i < \alpha$, where α represents its default threshold. If $p_i = \text{PD}$ is the unconditional probability of default (independent of the value of factor Z) of such borrower, then $\rho_i = \Phi(\alpha)$, where $\Phi(.)$ represents the standard normal cumulative probability distribution.

The appropriate default threshold (α) for average conditions is determined by applying a reverse of the Merton model to the unconditional PD. Because in Merton's model the default threshold and the borrower's

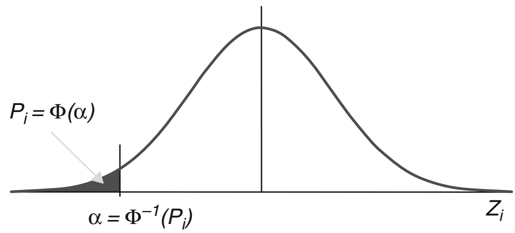

Figure 2.1 Asset value returns of firm i

PD are connected through the normal distribution function, the default threshold can be inferred from the PD by applying the inverse normal distribution function to the unconditional PD in order to derive the model input from the already known model output. Then, $\alpha = \Phi - 1(p_i)$.

If the dynamic of the macroeconomic factor X in the following year is known (X^*), then borrower *i* becomes insolvent if:

$$Z_i = w \cdot X^* + \sqrt{1-w^2} \cdot \varepsilon_i < \alpha \tag{2.4}$$

and

$$\varepsilon_i < \frac{\alpha - w \cdot X^*}{\sqrt{1-w^2}} = \frac{\Phi^{-1}(p_i) - w \cdot X^*}{\sqrt{1-w^2}} = \tag{2.5}$$

Because ε_i follows a normal standard distribution, the probability of default for borrower *i*, given $X = X^*m$, is:

$$\begin{aligned} p\left(default_i \middle| X = X^*\right) &= p\left(\varepsilon_i < \frac{\Phi^{-1}(p_i) - w \cdot X^*}{\sqrt{1-w^2}}\right) \\ &= \Phi\left[\frac{\Phi^{-1}(p_i) - w \cdot X^*}{\sqrt{1-w^2}}\right] \end{aligned} \tag{2.6}$$

Hence, the conditional probability of default for borrower *i* is a function $\Phi(.)$ of the unconditional PD (p_i), of the correlation parameter (w), and of the systematic factor (X^*).

Because the portfolio is asymptotically fine-grained, given $X = X^*$, the observed default rate is equal to the conditional probability of default. In other terms, in a infinitely granular portfolio the idiosyncratic error tends to zero and the observed distribution tends to fit the theoretical one. Therefore, assuming an LGD of 100 percent,[9] (18) the conditional probability of default is the actual loss rate (l) that the loan portfolio will

experience if the systematic risk factor takes a value of X^*:

$$l\left(PD \middle| X = X^*\right) = LGD \cdot \Phi\left[\frac{\Phi^{-1}\left(p_i\right) - w \cdot X^*}{\sqrt{1-w^2}}\right] \tag{2.7}$$

Yet the value of the systematic risk factor X is unknown. According to the Basel Committee, the systematic risk factor must assume an appropriately conservative value in order to calculate the capital requirements for regulatory purposes. Given that X is normally distributed, this is accomplished using the equation above to detect a loss value *L*, which shall only be exceeded in x percent of cases, where x represents a sufficiently small percentage of cases in which regulators accept that the value of losses is higher than the amount of capital and reserves. Thus, the smaller the value of x, the higher the capital requirements. Hence, the following equation provides the amount of capital and reserves necessary to cover 1 – x percent of all possible losses:

$$L = LGD \cdot \Phi\left[\frac{\Phi^{-1}\left(p_i\right) - w \cdot \Phi^{-1}(x)}{\sqrt{1-w^2}}\right] \tag{2.8}$$

The Basel Committee sets a value of x equal to 0.1 percent; that means that under the IRB approach capital and reserves might be inadequate to cover losses in one case out of one thousand:

$$L = LGD \cdot \Phi\left[\frac{\Phi^{-1}\left(p_i\right) - w \cdot \Phi^{-1}(0.1\%)}{\sqrt{1-w^2}}\right] \tag{2.9}$$

Also, parameter *w*, which determines the value of the asset correlation ($\rho = w^2$), plays a relevant role in determining the capital requirement for given levels of the PD. In fact, the degree of the obligor's exposure to the systematic risk factor is expressed by the asset correlation that shows how the value of assets of one borrower depends on the value of assets of another. Thus, the correlations might be described as the dependence of the value of the assets of a borrower on the general state of the economy, and all borrowers are linked to each other by this single risk factor.

The asset correlations determine the shape of the risk-weight formulas: the higher the parameter *w*, the higher the capital requirements. In fact, the more the loans of a portfolio are sensitive to the macroeconomic risk factor *Z*, the more they tend to default simultaneously, making extreme losses more likely. The asset correlations are asset-class dependent, because different borrowers and/or asset classes show different degrees of dependency on the overall economy.

Hence, the Basel Committee has selected different ρs for the sub-portfolios of similar loans:

The supervisory asset correlations of the Basel II's risk-weight formula for corporate, bank and sovereign exposures come from the analysis of datasets from G-10 supervisors who have developed their own rating systems for corporates. Time series of these systems determine default rates as well as correlations between borrowers. The analysis of these time series discloses two systematic dependencies: first, asset correlations decrease with increasing PDs; the higher the PD, the higher the idiosyncratic (individual) risk components of a borrower; the default risk depends less on the overall state of the economy and more on individual risk drivers. And second, asset correlations increase with firm size: the larger a firm, the higher its dependency upon the overall state of the economy, and vice versa. Smaller firms are more likely to default for idiosyncratic reasons.

The asset correlation function uses two limit correlations, 12 percent and 24 percent, for very high and very low PDs (100 percent and zero, respectively). Correlations between these limits are modeled by an exponential weighting function that displays the dependency on the PD. In addition to the exponentially decreasing function of the PD, correlations are adjusted to firm size that is measured by annual sales. The linear size adjustment affects borrowers with annual sales between 5 million and 50 million; for borrowers with 50 million annual sales and above, the size adjustment becomes zero, whereas for borrowers with 5 million or less annual sales, the size adjustment takes the value of 0.04, thus lowering the asset correlation from 24 percent to 20 percent (best credit quality) and from 12 percent to 8 percent (worst credit quality). The asset correlation function for bank and sovereign exposures is the same as for corporate borrowers, except the size adjustment factor does not apply.

The capital quantified in Equation 8 covers every possible future loss up to a given confidence level (99.9 percent of cases). Therefore, the resulting capital requirement covers all possible losses (L) except for 0.1 percent of the worst cases. Such losses include both expected losses (EL) and a percentage of unexpected losses (UL) that happen in extreme scenarios: $L = EL + UL$.

Nevertheless, banks are expected to cover their EL on an ongoing basis by, for example, provisions and write-offs, because it represents a cost component of the lending business. The UL, on the other hand, relates to potentially large losses that rarely occur.

According to this concept, capital requirement might only be needed for absorbing the UL, and accordingly the EL has to be taken out. The

Basel II framework accomplishes this by defining the EL as the product of the bank-reported average PD and the bank-reported downturn LGD for an exposure (EL = PD* LGD). Note that this definition leads to a higher EL than is implied by a statistically expected loss concept, because the downturn LGD is generally higher than the average LGD. Subtracting the EL from the conditional expected loss for an exposure yields a UL-only capital requirement:

$$UL = LGD \cdot \Phi\left[\frac{\Phi^{-1}\left(p_i\right) - w \cdot \Phi^{-1}(0.1\%)}{\sqrt{1-w^2}}\right] - PD \cdot LGD \tag{2.10}$$

However, in order to preserve a prudent level of overall funds, banks have to demonstrate that they build adequate provisions against the EL.

Equation 10 has to be further adjusted to take into account the impact that the loan maturity plays on risk. In the ASFR default-mode model, losses are incurred on a loan only if the borrower defaults. However, the mark-to-market value of long-term credits might decrease simply because the borrower's rating is downgraded. Given that credit portfolios consist of instruments with different maturities, the Basel Committee requires the bank to account for the downgrading risk that is higher, the longer the maturity of the loan.

Therefore, the maturity adjustment represents the additional capital requirement due to potential downgrades and the loss of the market value of loans. Downgrades are more likely in case of long-term credits and hence the corresponding capital requirements are higher than for short-term credits. Moreover, maturity effects are stronger with low PDs than high, because empirical evidence says that low PD borrowers have more room for downgrading than do high PD borrowers. Consistent with these considerations, the Basel maturity adjustments are a function of both maturity and the PD, and they are higher (in relative terms) for low PD than for high PD borrowers.

Given the specific aim of this book, the specification of the retail risk-weight curves is worth focusing on because Basel II treats it specifically. The retail risk weights differ from the corporate risk weights in two respects: first, the asset correlation assumptions are different; second, the retail risk-weight functions do not include maturity adjustments.

The asset correlations that determine the shape of the retail curves are reverse-engineered from economic capital figures from large internationally active banks, and historical loss data from supervisory databases of the G-10 countries. Both datasets contain matching PD and LGD values per economic capital or loss data point.

Both analyses show significantly different asset correlations for different retail asset classes. They lead to the three retail risk-weight curves for residential mortgage exposures, qualifying revolving retail exposures, and other retail exposures respectively. The three curves differ with respect to the applied asset correlations: relatively high and constant in the residential mortgage case, relatively low and constant in the revolving retail case; and, similarly to corporate borrowers, PD-dependent in the other retail case.

In the above analysis, both the economic capital data from banks and the supervisory loss data time series implicitly contain maturity effects. Consequently, the reverse-engineered asset correlations implicitly contain maturity effects as well, as the latter are not separately controlled for. In the absence of sufficient data for retail borrowers (similar to the risk premiums used to deriving the time structure of PDs for corporate exposures), this control would be difficult in any case. Thus, the maturity effects have been left as an implicit driver in the asset correlations, and no separate maturity adjustment is necessary for the retail risk-weight formulas.

The implicit maturity effect also explains the relatively high mortgage correlations: not only are mortgage losses strongly linked to the mortgage collateral value and the effects of the overall economy on that collateral, but they have long maturities that drive the asset correlations upwards as well. Both effects are less significant with qualifying revolving retail exposures and other retail exposures, and thus the asset correlations are significantly lower.

To conclude the analysis of the risk-weight functions, it must be also said that to attain its objective of broadly maintaining the aggregate level of minimum capital requirements while also providing incentives to adopt the more advanced risk-sensitive approaches of Basel II, the Basel Committee decided to apply a scaling factor σ to the risk-weighted asset amounts for credit risk under the IRB approach. The current best estimate of the scaling factor using quantitative impact study data is 1.06.

The final version of the formula for the calculation of capital requirement (K) for each exposure, including both the maturity adjustment (m) and the scaling factor (σ) is the following:

$$K = \mathrm{m} \cdot \sigma \cdot \left\{ LGD \cdot \Phi \left[\frac{\Phi^{-1}(p_i) - w \cdot \Phi^{-1}(0.1\%)}{\sqrt{1 - w^2}} \right] - PD \cdot LGD \right\} \cdot EAD \tag{2.11}$$

Minimum requirements

To be eligible for the IRB approach a rating system must meet certain minimum requirements at the onset and on an ongoing basis. Bearing in mind that the term rating system comprises all of the methods, processes, controls, data collection and IT systems that support the assignment of internal risk ratings to borrowers, and the quantification of default and loss estimates, the requirements that a bank's rating systems must fulfill have either a quantitative or a qualitative nature.

The overarching principle behind these requirements – that cut across asset classes – is that rating and risk estimation systems and processes provide for a meaningful assessment of borrower and transaction characteristics, a meaningful differentiation of risk, and reasonably accurate and consistent quantitative estimates of risk.

Among the quantitative minimum requirements that are particularly important are those that pertain to the rating system design and to the quantification of risk parameters.

As for the design of rating systems, an IRB system must have two distinct dimensions: the risk of borrower default, and transaction-specific factors. With reference to the first dimension, separate exposures to the same borrower must be assigned to the same borrower grade,[10] irrespective of any differences in the nature of each specific transaction. The second dimension must reflect transaction-specific factors, such as collateral, seniority, product type, etc. In particular, for banks using the advanced approach, facility ratings must reflect exclusively LGD.

Banks must have a meaningful distribution of exposures across grades, with no excessive concentrations, on both its borrower-rating and its facility-rating scales. To meet this objective, a bank must have a minimum of seven borrower grades for non-defaulted borrowers and one for those that have defaulted. There is no specific minimum number of facility grades for banks using the advanced approach for estimating LGD; nonetheless, a bank must have a sufficient number of facility grades to avoid grouping facilities with widely varying LGDs into a single grade. The criteria used to define facility grades must be grounded in empirical evidence.

Banks must have specific rating definitions, processes and criteria for assigning exposures and facilities to grades within a rating system.[11] Rating definitions must be written, clear and detailed enough to allow third parties, such as internal audit and supervisors, to understand the assignment of ratings, to replicate rating assignments and evaluate the appropriateness of the grade/pool assignments. To assign exposures and

facilities to grades, banks must use all relevant and material available information: the less information a bank has, the more conservative must be its assignments of exposures to grades.

With reference to the quantification of risk parameters, banks must fulfill additional requirements when they adopt statistical models to estimate PDs, LGDs, or EADs. Mechanical rating procedures are widely adopted by banks since they allow the minimization of the idiosyncratic errors made by rating systems in which human judgment plays a large role. Nevertheless, credit scoring models and other automatic rating procedures generally use only a subset of available information, and mechanical use of limited information also is a source of rating errors. Against this backdrop, Basel II recognizes statistical models as the basis of rating assignments, and of loss characteristics' estimation, provided that sufficient human judgment and oversight ensure that all relevant information, including that which is outside the scope of the model, is taken into account, and that the model is used appropriately.[12]

Banks must have written guidance describing how human judgment and model results are to be combined, and procedures for human review of model-based rating assignments. Such procedures should aim at preventing errors associated with known model weaknesses and must also include credible ongoing efforts to improve the model's performance.

Basel II sets specific standards for retail rating system that must be oriented to both borrower and transaction risk, and must capture all relevant borrower and transaction characteristics. Banks must assign each exposure that falls within the definition of retail for IRB purposes into a particular pool. Banks must demonstrate that this process provides for a meaningful differentiation of risk, provides for a grouping of sufficiently homogenous exposures, and allows for accurate and consistent estimation of loss characteristics at pool level.

For each pool, banks must estimate PD, LGD, and EAD. Multiple pools may share identical PD, LGD and EAD estimates. At a minimum, banks should consider the following risk drivers when assigning exposures to a pool: *borrower risk characteristics* (for example borrower type, demographics such as age/occupation); *transaction risk characteristics*, including product and/or collateral types (for example loan-to-value measures, seasoning, guarantees; and seniority, such as first vs. second lien); and *delinquency of exposure* (banks are expected to separately identify exposures that are delinquent and those that are not).

For each pool identified, banks must be able to provide quantitative measures of loss characteristics (PD, LGD, and EAD). The level of differentiation for IRB purposes must ensure that the number of exposures

in a given pool is sufficient to allow for meaningful quantification and validation of the loss characteristics at the pool level. There must be a meaningful distribution of borrowers and exposures across pools. A single pool must not include an undue concentration of the bank's total retail exposure.

Among qualitative minimum requirements, it is worth mentioning those aimed at preserving the integrity of rating process. In particular, rating assignments and periodic rating reviews must be approved by an internal function that does not directly benefit from the extension of credit. Given that the independence of the rating assignment process can be achieved through a range of practices, these operational processes must be documented in the bank's procedures in order to allow supervisors to assess them.[13] Borrowers and facilities must have their ratings refreshed on at least an annual basis.[14]

More in general, qualitative requirements affect corporate governance and oversight of rating systems. All material aspects of the rating and estimation processes must be approved by a bank's board of directors and senior management that must possess a general understanding of the rating system. Management must also ensure, on an ongoing basis, that it is operating properly. Moreover, banks must have independent credit risk control units that are responsible for the design, implementation and performance of their internal systems. The unit(s) must be functionally independent from the personnel and management functions responsible for originating exposures.

Eventually, a key qualitative requirement relates to the use of internal system. Basel II requires that internal ratings and default and loss estimates play an essential role in the credit approval, risk management, internal capital allocations, and corporate governance functions of banks using the IRB approach. Ratings systems designed and implemented exclusively for the purpose of qualifying for the IRB approach and used only to provide inputs to capital requirements calculation are not acceptable.

Banks must document in writing the design and operational details of their rating systems. The documentation must evidence the bank's compliance with the minimum standards, and must address topics such as portfolio differentiation, rating criteria, responsibilities of parties that rate borrowers and facilities, definition of what constitutes a rating exception, parties that have authority to approve exceptions, frequency of rating reviews, and management oversight of the rating process. The organization of rating assignment, including the internal control structure, must also be documented.[15]

The set of minimum requirements designed to ensure the integrity of the internal risk assessments is not intended to dictate the form or operational detail of banks' risk management policies and practices; each national supervisor is responsible for developing review procedures for ensuring that banks' systems and controls are adequate to serve as the basis for the capital calculations.

Indeed, one of the greatest challenges posed by the revised capital framework, for both banks and supervisors, is validating the systems used to generate the parameters that serve as inputs to the IRB approach. In the context of rating systems, the term "validation" encompasses a range of processes and activities that contribute to an assessment of whether ratings adequately differentiate risk and whether estimates of risk components (PD, LGD and EAD) appropriately characterize the relevant aspects of risk.

Banks have the primary responsibility for validating their own credit systems, and consequently must demonstrate how they provide risk estimates and must confirm that processes for assigning risk estimates are likely to work as intended and continue to perform as expected. Thus, banks must have a regular cycle of model validation that includes monitoring of model performance and stability, and testing of model outputs against outcomes. Supervisors, on the other hand, must assess the credit institution's validation processes and outcomes, and may rely upon additional processes of their own design in order to have the required level of supervisory comfort or assurance. (BCBS, 2005)

There may be circumstances when a bank is not in complete compliance with all the minimum requirements. Where this is the case, the bank must produce a plan for a timely return to compliance, and seek approval from its supervisor. Failure to produce an acceptable plan or satisfactorily implement the plan leads supervisors to reconsider the bank's eligibility for the IRB approach. Furthermore, for the duration of any non-compliance, supervisors may consider the need for the bank to hold additional capital under Pillar 2 or take other appropriate supervisory action.

2.4 Toward Basel III and beyond

2.4.1 Taking stock of the Basel II framework

Basel II has presented merits as well as drawbacks and open issues. The advantages include the greater risk sensitivity of capital requirements, the incentive given to banks to improve their internal risk

management systems, and the creation of a common language of risk profiles that enhances both supervision and market discipline of banks' credit risk.

Some – often quoted – limitations of Basel II include its complexity and the related significant administrative difficulties in monitoring banks' implementation of IRB systems and their ongoing compliance with regulatory requirements. Some observers, also considering the procyclicality of the revised Accord (the exacerbation of the macroeconomic effects normally associated with risk-sensitive bank capital requirements), conclude that the potential benefits of the IRB approach are likely to be outweighed by its risk and shortcomings (Tarullo, 2008).

Actually, the criticism to the overly complexity of Basel II seems to be unjustified. What appears to be complex is the topic of Basel II (that is, risk management) and not Basel II in itself. Hence, length and complexity are unavoidable, when tackling this subject in an exhaustive and in-depth manner (Resti, Sironi, 2007).

The concern relating to the procyclicality of Basel II is more grounded. Indeed, all regimes with minimum capital requirements have the potential to generate procyclical effects because capital available to meet the requirements becomes scarcer in recessions as banks make provisions and write off defaulted loans. Hence, in order to maintain the ratio between capital and risk-weighted assets, banks would end up granting less credit to the economy, thus deepening the recession. Likewise, strong economic growth is associated with higher creditworthiness of borrowers and lower loan-loss provisions and write-offs. Capital ratios decrease, allowing banks to provide more credit to the economy.

The new element under Basel II is the potential for capital requirements on non-defaulted assets to increase in recession due to borrower ratings' migration. Under the revised framework, procyclicality depends on the evolution of both default rates and migration rates. Hence, capital requirements based on ratings may amplify the fluctuations of the economic cycle with respect to a system of capital ratios based on fixed weights (Basel I).

The Basel Committee has adopted some precautionary measures to mitigate such an effect. Firstly, the procyclicality in Basel II has been dampened by adjusting the level of correlation between ratings and risk weights. Under the standard approach, the increase in the capital requirement due to a downgrading is generally small. Such a weighting system is wanted as, even though it represents the relationships between rating and risk in a somewhat unrealistic way, it does reduce procyclicality. Under the IRB approach, a key parameter of regulatory functions

connecting PDs with the minimum capital requirements is asset correlation: the higher the vale of ρ, the smaller the diversification benefit and hence, for a given PD, the higher the capital requirement. As mentioned above, a system of variable ρ values is in place: for corporate exposures, these start at 24% and decrease to 12% for borrowers with a higher PD. Similarly for "other retail" exposures, ρ values range between 16% and 3%. Consequently as PDs increase, the regulatory functions produce a less significant increase in capital requirements. This reduces the overall degree of procyclicality of the system.

However, the extent of the Basel II additional procyclicality depends not only on the design of capital requirements but also on the nature of their rating systems. Indeed, the degree of procyclicality of capital requirements depends on the process adopted by banks to assign ratings to their borrowers: a point-in-time (PIT) approach or a through-the-cycle (TTC) one. A PIT assessment reflects the current condition of the economic cycle, and it is expected to change as the state of the economy evolves. A TTC rating is, however, likely to be more stable despite fluctuations in the economic cycle. Banks seem to prefer PIT rating systems, due to the fact that they are more manageable for credit management purposes, and especially for pricing loans. PIT rating systems are more proyclical, since more frequent migrations among rating grades are more likely.

The Basel Committee explicitly addressed this issue by stating that although the time horizon used in PD estimation is one year, banks are expected to use a longer time horizon in assigning ratings, and that banks must assess the borrowers' ability to perform despite adverse economic conditions or the occurrence of unexpected events.

Despite the valuable purpose (mitigating the procyclicality of capital requirements), this requisite condition is in practice hard to achieve. A TTC rating system is difficult to implement, given the difficulties of foreseeing unexpected events, and to monitor, given the technical problems in validating the outputs of TTC models on an ex post basis by means of statistically significant back tests. Moreover. a TTC rating process might not fit credit management needs, thus creating a gap between "regulatory" and "management" ratings.

This and other major implementation issues, including how to achieve a level playing fields among banks adopting the different options made available by the new framework, were still open when the advent of the financial crises triggered a debate over whether an already fully implemented Basel II framework would have mitigated or exacerbated it.

2.4.2 The Basel Committee's response to the financial crisis

Basel II never came into effect properly. Since July 2009, the BCBS has adopted amendments to the Basel II framework to address the lessons of the financial crisis whose depth and severity had been amplified by weaknesses in the banking sector, such as excessive leverage, inadequate and low-quality capital, and insufficient liquidity buffers. Furthermore, the crisis was exacerbated by a procyclical deleveraging process and the interconnectedness of systemically important financial institutions. (BCBS, 2010)

Hence, the BCBS has developed a reform program aimed at improving the banking sector's ability to absorb shocks arising from financial and economic stress, no matter what the source, thus reducing the risk of spillover from the financial sector to the real economy.

The reforms seek to strengthen micro prudential regulation, which should help raise the resilience of individual banking institutions in periods of stress. The reforms also have a macro prudential focus, addressing the system-wide risks which can build up across the banking sector, as well as the procyclical amplification of these risks over time. These micro and macro prudential approaches to supervision are interrelated, as greater resilience at individual bank level reduces the risk of system-wide shocks.

The new global standards, referred to as Basel III, consist of the following building blocks:

- Raising the quality of capital to ensure banks are better able to absorb losses on both a going concern and a gone concern basis;[16]
- Increasing the risk coverage of the capital framework, in particular for trading activities, securitizations, exposures to off-balance sheet vehicles and counterparty credit exposures arising from derivatives;[17]
- Raising the level of the minimum capital requirements, including an increase in the minimum common equity requirement from 2 percent to 4.5 percent and a capital conservation buffer of 2.5 percent, bringing the total common equity requirement to 7 percent;
- Introducing an internationally harmonized leverage ratio to serve as a backstop to the risk-based capital measure and to contain the build-up of excessive leverage in the system;
- Promoting the build-up of capital buffers in good times that can be drawn down in periods of stress, including the aforesaid capital conservation buffer as well as a countercyclical buffer to protect the banking sector from periods of excess credit growth;

- Introducing minimum global liquidity standards consisting of both a short-term liquidity coverage ratio and a longer-term, structural net stable funding ratio;
- Raising standards for the supervisory review process (Pillar 2) and public disclosures (Pillar 3), together with additional guidance in the areas of sound valuation practices, stress testing, liquidity risk management, corporate governance and compensation.

It is worth noting that the fundamental approach introduced by Basel II for determining credit risk-weighted assets through internal models has not changed. In fact, Basel III is essentially a new layer built over the old Basel II architecture, hence Basel III has inherited some of the problems of Basel II. The main one is the whole concept of risk weighting: some assets are riskier than others, and banks should hold more capital against risky assets.

Ideally, Basel II assumes that banks are in the best position to measure their own risks, and that a regulatory framework that aligns regulatory capital requirements with the risk being taken is to be desired. In practice, the regulatory framework might push banks toward avoiding measurable risks and hence into risks that banks, and supervisors, cannot easily measure within the Pillar 1 framework. In general, the recent crises raised doubts that the risks associated with complexity and dynamics of large banks' activities can be effectively contained by detailed, even sophisticated, rules.

Indeed, the complexity of internationally active banks' risk profile places a greater emphasis than ever before on the rigouressness and accuracy of banking supervision. If the Basel arrangements are to provide assurance that the risks posed to international financial stability by banks of all member countries are adequately contained, then it is essential that more attention be paid to the supervisory process. The Basel Committee has reaffirmed the central role of supervision, stating that in an environment of continuously rapid financial innovation, stronger capital and liquidity standards must be accompanied by better risk management and supervision. (BCBS, 2010) (18)

Furthermore, the Basel Committee instigated several initiatives aimed at reducing procyclicality, considered by many observers as the main drawback of the Basel framework. These include the introduction of the leverage ratio to help contain the build-up of excessive leverage in the system during periods of credit expansion, as well as the use of stressed inputs for the calculation of value at risk and counterparty credit risk. On top of that, the goal of mitigating procyclicality in the banking and

broader financial system is pursued by the build-up in good times of buffers that can be drawn down in periods of stress.

First, banks are required to hold a capital conservation buffer comprising common equity of 2.5 percent. This buffer above the minimum could be used to absorb losses during periods of financial and economic stress. However, as a bank's capital level moves closer to the minimum requirement, the conservation buffer would impose a constraint on the bank's discretionary distributions. Retaining a bigger proportion of earnings during a downturn will help ensure that capital remains available to support the bank's ongoing business operations during the period of stress.

In addition, banks will be required to maintain a countercyclical buffer within a range of 0 to 2.5 percent, consisting of common equity or other fully loss-absorbing capital. Its purpose is to achieve the macro prudential goal of protecting the banking sector in periods of excess aggregate credit growth. For any given country, this buffer would only come into effect when there was excess credit growth resulting in a system-wide build-up of risk. The countercyclical buffer, when in effect, would be imposed as an extension of the conservation buffer range. Conversely, the buffer would be released when, in the judgment of the authorities, the released capital would help absorb losses in the banking system that posed a risk to financial stability. This would help reduce the risk of available credit being constrained by regulatory capital requirements.

The introduction of capital buffers, if properly implemented, could help address the main limitation of the current regulatory framework. As mentioned above, to mitigate the procyclicality embedded in a regulatory framework based on risk-sensitive capital requirements, banks are required to use ratings that reflect borrowers' ability to perform over a time horizon longer than one year, ideally covering at least one complete economic cycle. At first sight, this approach can seem valid. But then comes to mind the well established Tinbergen principle, which says that it is necessary to have at least as many instruments as objectives (Tinbergen, 1952).

Indeed, banks are granted permission to use their internal risk measurement system for regulatory purposes provided that they play an essential role in the risk management processes (the "Use Test"). This serves the purpose of demonstrating that banks themselves trust their own internal risk measures. However, if banks must use ratings in their decision-making process (for example, a bank must decide whether or not to extend a loan), they would need tools to assess the borrower's current creditworthiness rather than its backward-looking, long-term

average probability of default. Here is the paradox: the rating of a single borrower should take into account all available, relevant and updated information – but as far as the borrower's portfolio is concerned, a supervisor's expectation is that risk measures are not heavily dependent on current conditions.

This issue can also be viewed from another perspective of the relationship between banks and supervisors. Stress has already been laid on the importance of rating systems' validation that includes monitoring of model performance and stability, and testing of model outputs against outcomes. If supervisors complain that probabilities of default are systematically different from observed default rates, banks might argue that risk measures compliant with supervisory requirements should be compared with certain multiperiodal default rates rather than with current outcomes in order to assess internal models' performance. If, then, supervisors observe that management practices (for example, provisioning) do not reflect internal risk estimates, the bank might reply that its operations cannot be based on long-term measures.

After capital buffers become effective, banks could be required to maintain any difference between risk estimates and actual default rates within a reasonable, limited margin of error, and to ensure that management choices are based on such internal estimates. This way, the confidence of supervisors and investors in these risk measures would be strengthened. However, Basel III adds capital buffers to the existing provisions, and the possibility for banks to use PIT risk measures cannot be taken for granted.

More generally, even before the new regulation on capital buffers comes into force, one further problem may arise. In fact, should the market perceive that the capital ratio including the capital conservation buffer (7 percent) is never to be breached, dynamic buffers would no longer exist, and ratings would once again become the only instrument to achieve the two different objectives: measuring the actual creditworthiness of borrowers and mitigating procyclicality. The probable result would be that both of them would remain out of reach.

To conclude, the success of international capital standards in preventing banking distress has been mixed. Basel I regulatory rules were arbitraged due to their risk insensitivity. This gave rise to Basel II with its greater focus on risk calibration. But Basel II collapsed under the weight of the recent crisis. Amendments have since been applied through Basel III. Historical experience and predictable future trends suggest this is unlikely to be the end of road.

Notes

The views expressed in this chapter are those of the author and do not involve the responsibility of the Bank of Italy.

1. Issued and fully paid ordinary shares/common stock and perpetual noncumulative preference shares.
2. Reserves created or increased by appropriations of retained earnings or other surplus, e.g. share premiums, retained profit, general reserves, and legal reserves.
3. The definition of eligible regulatory capital was clarified in the October 27, 1998, press release on "Instruments eligible for inclusion in Tier 1 capital."
4. One of the main concerns of the banking international community was the advantage of Japanese banks that operated with an apparently lower capital to total assets ratio than their competitors in developed countries (G-10). The latter, especially British and US banks during the 1980s, had gradually lost shares of the international bank loans market. Analysis of the impact of the 1988 Accord on international banks showed that the average capital to total assets of Japanese banks was 2.1 percent, versus 3.3 percent for Germany, 4.9 percent for the USA, 5.1 percent for Canada, 5.4 percent for the UK, and 6.3 percent for Switzerland. However, including undisclosed reserves, Japan's ratio increased to 12.4 percent.
5. The OECD group comprises, for the purpose of the 1988 Accord, all members of the OECD or countries that have concluded special lending arrangements with the International Monetary Fund that are associated with the Fund's General Arrangements to Borrow, and which have not rescheduled their external sovereign debt within the previous five years.
6. When this approach was adopted, the Basel Committee recognized the shortcoming that some countries might not merit inclusion on grounds strictly related to default risk, but might be included in the preferential group while potentially high credit quality countries outside the OECD might be excluded. However, when adopted, the OECD/non-OECD approach was determined to be the most workable proxy for identifying countries that should be eligible for preferential risk-weighting treatment.
7. The weightings to be used for these purposes do not include the modified treatment potentially available for domestic currency lending to the bank's own government or central bank.
8. In order for banks to obtain capital relief for any use of CRM techniques, all documentation used in collateralized transactions and for documenting on-balance sheet netting, guarantees, and credit derivatives must be binding on all parties and legally enforceable in all relevant jurisdictions. Banks must have conducted sufficient legal review to verify this compliance and have a well-founded legal basis to reach this conclusion, and undertake such further review as necessary to ensure continuing enforceability.
9. In contrast to the treatment of PDs, Basel II does not contain an explicit function that transforms average LGDs expected to occur under normal business conditions into conditional LGDs consistent with an appropriately conservative value of the systemic risk factor. Instead, banks are asked to report LGDs

that reflect economic downturn conditions in circumstances where loss severities are expected to be higher during cyclical downturns than during typical business conditions. In general, LGDs take values lower than 100 percent, either predetermined in the foundation approach or estimated by the bank in the advanced.

10. The grade description and criteria must be sufficiently detailed to allow those charged with assigning ratings to consistently assign the same grade to borrowers or facilities posing similar risk. This consistency should exist across lines of business, departments and geographic locations. The criteria must also be consistent with the bank's internal lending standards and its policies for handling troubled borrowers and facilities.
11. The burden is on the bank to satisfy its supervisor that a model has good predictive power and that regulatory capital requirements will not be distorted as a result of its use. Moreover, the bank must have in place a process for vetting data inputs into a statistical default or loss prediction model which includes an assessment of the accuracy, completeness and appropriateness of the data specific to the assignment of a rating. The bank must also demonstrate that the data used to build the model are representative of the population of the bank's actual borrowers or facilities.
12. For rating assignments based on expert judgment, banks must identify the situations in which bank officers may override the outputs of the rating process, including how and to what extent such overrides can be used and by whom. For model-based ratings, the bank must have guidelines and processes for monitoring cases where human judgment has overridden the model's rating, variables were excluded or inputs were altered. These guidelines must include identifying personnel that are responsible for approving these overrides. Banks must identify overrides and separately track their performance.
13. Certain credits, especially higher risk borrowers or problem exposures, must be subject to more frequent review. In addition, banks must initiate a rating review if material information on the borrower or facility comes to light. Banks must have an effective process to obtain and update relevant and material information on the borrower's financial condition, and on facility characteristics that affect LGDs and EADs (such as the condition of collateral).
14. Banks must document the rationale for their choice of internal rating criteria and must be able to provide analyses demonstrating that rating criteria and procedures are likely to result in ratings that meaningfully differentiate risk. Rating criteria and procedures must be periodically reviewed to determine whether they remain fully applicable to the current credit portfolios and to external conditions.
15. The global banking system entered the crisis with an insufficient level of high quality capital. Banks were forced to rebuild their common equity capital bases in the midst of the crisis at the point when it was most difficult to do so. The crisis also revealed the inconsistency in the definition of capital across jurisdictions and the lack of disclosure that would have enabled the market to fully assess and compare the quality of capital across institutions. The Basel Committee has adopted a new definition of capital. Higher quality capital means more loss-absorbing capacity, allowing banks to better withstand periods of stress. A key element of the new definition is the greater focus on common equity, the highest quality component of a bank's capital. Therefore,

the Committee has adopted a stricter definition of common equity, requiring regulatory capital deductions to be taken from common equity rather than from Tier 1 or Tier 2 capital, as is currently the case. As a result, it will no longer be possible for banks to display strong Tier 1 capital ratios with a limited common equity net of regulatory deductions.

16. Further to raising the quality and level of the capital base, the Committee has addressed the need of capturing all material risks in the capital framework. In fact, during the crisis, many risks were not appropriately covered in the Basel II regime. For example, some banks held significant volumes of complex, illiquid credit products in their trading books without a commensurate amount of capital to support the risk. Indeed, failure to capture major on- and off-balance sheet risks, as well as derivative related exposures, was a key factor that amplified the crisis. In response, in July 2009, the Committee introduced a set of enhancements to the capital framework that considerably strengthen the minimum capital requirements for complex securitizations as well as the rules that govern capital requirements for trading book exposures (so-called Basel 2.5). The revised trading book framework, on average, requires banks to hold additional capital of around three to four times the old capital requirements, thus better aligning regulatory capital requirements with the risks in banks' trading portfolios. The Committee has also increased capital requirements for counterparty credit risk in response to significant losses due to the sudden deterioration in the credit quality of counterparties during the crisis.
17. In July 2009, the Committee conducted a review of the Pillar 2 supervisory review process to address several notable weaknesses that were revealed in banks' risk management processes during the financial crisis. The areas addressed include: firm-wide governance and risk management; capturing the risk of off-balance sheet exposures and securitization activities; managing risk concentrations; providing incentives for banks to better manage risk and returns over the long term; and sound compensation practices.

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3
Private Individuals: Credit Risk Modeling

Corrado Giannasca and Tommaso Giordani

3.1 Introduction

In the old good days, the main innovation in banking was air conditioning. Since then, the financial industry has experienced many changes. Of those changes, statistical credit risk modeling is one of the most influential. Retail banking strategy has evolved toward a profit maximizing, industrial processing model where efficiency, speed, and control are key success factors. In this context, senior management has been very receptive to the development of a statistical decision framework.[1] Increasingly complex laws and regulations have also required the need for a formalized risk measurement and control framework. In addition, the diversification by both countries and products has added further intricacies. In this chapter, we assess the pros and cons of credit risk modeling for operational processes, policy definitions, business goal setting, and organizational change. We leave the statistical and analytical aspects of the modeling to the well established technical literature.

3.2 Retail credit risk

Retail credit entails a huge number of operations and individuals where a single loan has only a negligible impact on the relevant economic dimensions: scale of activities, revenues, and costs.

These characteristics make statistical reasoning highly effective for decision making. The part development of quantitative models to support day-by-day decisions in banks' operational processes has become a central feature of the industry. Currently, despite the deep crisis post 2007, all banks and financial institutions still maintain and continue to build up large portfolios of credit cards, personal loans, car loans,

overdraft lines and mortgages that can contribute significantly to the overall profitability of the business.

Credit risk management has evolved both in its complexity and its impact on economic results. Credit risk management not only sets the rules and tools for customers' creditworthiness evaluation and monitoring, but also creates the planning and forecasting building blocks for the calculation of the impairment of loans, the modeling of risk-weighted asset (RWA) parameters, risk–reward measurement and optimization – including pricing and profitability. A deep change in the organizational structures in banking has accompanied this evolution in scope and responsibility by creating an increasing matrix of the reporting network with a loose hierarchical structure. The impacts on operational areas of credit risk management have become even more pervasive by setting the rules on risk appetite and concentrations, customer/product-specific policies, score cut-off setting, risk-based pricing, collections and recoveries goal setting, and many other processes. The increasing scale of operations for systemically important financial institutions exposes the bank portfolios to macroeconomic conditions that determine the additional need to incorporate some measure of the impact of economic cycles on the expected credit performance and to evaluate the effect of different levels of stress on RWAs and economic capital.

3.2.1 Judgmental versus statistical models

Lenders assess creditworthiness through careful scrutiny of the applicant(s) for a specific credit facility. There are two main evaluation frameworks applied to this goal: the *relational* and *transactional* models. The relational model relies on decentralized customers that are tightly coupled with the local economic and social fabric. The decision to grant credit comes after a long-term relationship between the bank and the customer that has built up a level of trust. In the case of a new customer, the decision is based on the network of the customer's local relations that support and, in some sense, guarantee his or her creditworthiness.

The transactional model on the other hand is based on the observation of the customer's behavior through the data recorded in the bank's database in accessing and using credit products. The accumulation of data is the main source of information to evaluate creditworthiness and to make the decision on whether to extend or deny credit facilities, in many cases without any personal contact between the decision maker and the customer.

The five C's of credit evaluation (*Character*, *Capacity*, *Capital*, *Collateral*, and *Conditions*) change their meaning in the two different contexts. The

relational credit analysis relies on human judgment to evaluate creditworthiness – a credit officer carries out the analysis of credit applications in light of his or her past experience and actual knowledge of the customer in relation to the bank's established policies. The transactional credit analysis is, in contrast, based mainly on the statistical modeling of a huge amount of current and historical data stored in computer systems; the model development is carried out by statistics professionals who are usually disconnected from local business conditions and the customers' interaction environment, as is often observed also for the credit underwriting specialists. The main advantages are related to the uniformity of treatment, automation of processes, and cost savings. The drawbacks are an excessive mechanical application of the statistical methods that does not consider whether any decision comes from an interaction between the lender and the borrower in a broader informational environment that contains many asymmetries that models cannot completely incorporate and resolve. Furthermore, the modeling activity does not take place at the local level where real life is observed. Thus, the decision is devoid of any relational input.

These apparent drawbacks are compensated for by the controls, metrics and simulation capabilities embedded in the framework, where measurable credit risk can more predictably drive impairment costs which largely impact the profitability of the banking business (it is in fact one of the most significant cost items on the profit & loss balance sheet section); this predictability makes senior management and shareholders happier.

3.2.2 Individual versus portfolio models

The world of credit risk modeling has evolved along with the development of two technical areas: the ICT infrastructure and data warehousing. These two developments have increased the capacity of data storage and data processing, enabling statistical techniques to be applied to these large data repositories in order to extract significant and useful information. The heavy investment in technical tools was first directed at saving costs related to processing simple operations (think of cash withdrawal through a human teller vs. ATM). The natural by-product of electronic data processing has been its permanent storage and availability for out-of-operations analysis.

We can broadly identify two development areas based on data: the individual frame is based on models devoted to evaluating individual performance on relevant indicators (risk, revenue, take-up, activation, usage, cross-sell, attrition, etc.), whereas the portfolio frame is based

on forecasting aggregate behavior on specific metrics (prepayment, delinquency vintage, recoveries, profitability etc.).

The main assumption underlying the individual frame is that the customers' behavior can be observed and measured through quantitative characteristics that can identify the essential risk profiles through appropriate statistical classification techniques; it is also implicit in the approach that the near future will not be so far from the recent past.

The methodological approach that has prevailed in risk modeling to date is aimed at finding the best correlation between "explanatory" variables and the performance target instead of empirically validating a theoretical economic model of agent behavior. In that sense, the approach is just a useful tool to be used in decision-making processes to automate and speed up tasks, reduce costs, and increase marketing effectiveness.

These basic operational goals of the individual frame usually focus on the product rather than the customer. Market players have always had risk models in place for mortgages, loans, credit cards, car financing and overdraft lines; less common are models implemented at the customer level that determine, for example, the overall creditworthiness of the individual and then split his or her credit repayment capacity between different products. This is due to the complexity arising from data requirements and the lack of an established methodology from which to derive such models.

3.2.3 The critical role of data

The transactional approach relies heavily on data. A relatively new IT discipline has contributed to support and develop this framework: data warehousing (DWH). Data must be treated specifically for business intelligence goals that take care of some critical aspects not always addressed in operational systems: integrity, standardization, coherence, usability, documentation, and historical data storage. Related professional figures, such as data architects and DWH specialists, have emerged to take care of the preparation and maintenance of the data structures needed for analysis and provide a bridge of expertise to connect purely technical IT professionals and business analysts with limited IT skills.

Data quality assumes a central role in every process to avoid the *garbage in – garbage out* effect not only for model development but more generally in data-based decision making. Data becomes a strategic resource critically impacting the competitive position, growth, and profitability of the financial institutions. From a model development and project management perspective, the usability and integrity of data is of paramount

importance: in a fragmented and unstructured environment, the analysts' time (up to 90% of a project schedule) is wasted collecting data from disparate sources, verifying and cleaning fields, documenting data generation processes, doing preliminary analysis and cross-checking. The revision of models becomes very slow and redevelopment costs very high, driving a suboptimal model lifecycle management especially for models that are more exposed to feedback loops (such as marketing, behavioral, and collection).[2]

3.2.4 Model monitoring

Any kind of model that is implemented in operational processes must be periodically monitored to assess the alignment of the actual outcomes with respect to the estimated ones. Also, any degradation or deviation from the expected results must be reported to senior managers for appropriate decisions (revise, recalibrate, and redevelop). The importance of monitoring cannot be underestimated because model usage affects the customer's behavior and any feedback effects must be detected, to trigger revisions. This is a specific task that should be implemented in an organizational unit different from the developmental one.

Model back-testing is also of paramount importance in assessing the robustness and stability of outcomes even in the presence of changes in the customer's economic conditions. In any case we must bear in mind that models are tools useful to help us define the parameters of our knowledge; they are not crystal balls.

3.3 Individual model framework and management

A reasonably general expression that represents the estimation of the probability of a certain relevant event is the following:

$$P(y_{it} = 1|X) = f\left(\sum_{m=0}^{M} \beta_m x_{im} + \sum_{l=0}^{L}\sum_{p=0}^{P} \beta_{lp} x_{ipt-l} + \sum_{l=0}^{L}\sum_{j=0}^{J} \nu_{jl} z_{jt-l} + \beta_{i,j} \mathrm{I}^{\mathrm{n}}(\mathrm{i,j}) + \varepsilon_{it}\right) \tag{3.1}$$

In this expression, there are M static independent variables (x_m), P dynamic variables (x_p) measured on each customer and J external measurements (z_j) related to the macroeconomic environment. Each variable (apart from static ones) is a function of time t. Significant interactions

($I^n(i,j)$) between independent variables can exist with functional form to be investigated, and ε_{it} is a random noise. In reality, the applied framework is considerably simplified, leading to significant model-risk impacts. Due to data limitations and lack of clear theoretical foundations, the final models usually neither completely investigate nor incorporate many dynamic aspects, macro-environment variables, and possible mixed, nonlinear interactions.

Usually models are conceived as part of a more complex decision-making process that takes place at the different stages in the management of the credit cycle. The best known models are application scorecards that evaluate the creditworthiness of customers requiring a new product. In reality there are many other tools devoted to portfolio management, either from a product development point of view (for example, optimization of the credit line, increase/decrease in revolving credit and overdraft, product up-grade, or cross-selling) or for credit control (early/intermediate stage delinquency collection and recoveries).[3] In portfolio management and adaptive control,[4] behavioral models play a much more critical role in the decision-making process.

As repeatedly stressed, the logic embedded in any scorecard tool is based on statistical, not logical, reasoning. The scorecard rank orders the performance of borrowers, but is not intended to explain the reasons for that performance. No causal link is assumed or investigated, and the predictive strength is the unique model-selection criteria. The predictive variables might not have any causal relation with the borrower's creditworthiness, so they can adversely impact an applicant evaluation or be unable to cope with complex behavioral patterns. These potential weaknesses must be taken into account for an intelligent use of the models by providing adverse impact mitigation through appropriate

Table 3.1 Model diffusion by product

Product	Application	Behavioral	Take-up	Collection
Mortgages	High	High	High	Medium
Personal loans	High	Medium	High	High
Salary secured loans	Low	Low	Low	Low
Car financing	High	Medium	High	High
Consumer credit	High	Low	High	High
Revolving cards	High	High	High	High
Current account overdraft	Medium	High	Medium	High

Source: Authors.

exception policies and/or dedicated decision trees in the automated decision environment.

The complexity in applying statistical models to credit decisions can be effectively addressed through the incorporation of their outcomes in a decision-support system. This tool consists of layers of software that are integrated into the operational IT infrastructure of the bank and that are dedicated to the automation (and iterative optimization) of complex decision trees in different areas of interest to optimize the critical credit-decision processes (see Giannasca, (2011), pp. 280, 287, 296).

Large international banks that do business in very different markets and countries face many additional challenges in maintaining a competitive advantage in decision science. Senior management has to set up a controlled and efficient organizational structure capable of the following tasks:

1. *Virtual team management*: Often the development of the model is centralized in one or more centers of excellence to leverage specialization, professional profiles and recruitment skills, and to minimize the turnover risk, while the data are local and maintained in diverse DWH structures. Operations are carried out on the local IT systems, but in some cases part of, or the whole process of development can be outsourced to specialized providers (see Table 3.2 for further insights). These complexities require assembling and effectively managing different specialists and team cultures, in most cases working in distant locations and several time zones apart.
2. *The leverage of business expertise*: In a geographically spread structure, different stages of market development, distribution channels, customer habits and pricing constraints can coexist and must be properly taken into account to maximize the business effectiveness of each specific technical solution.
3. *Compliance with legal and regulatory constraints*: Different markets usually have different levels of privacy provisions with respect to data collection and storage, pricing and commission constraints, supervisory requirements, disclosure and complaint management. Standardized solutions are not always optimal in these contexts.

The model deployment in the technical infrastructure of the bank is another critical task that deserves some consideration due to the disruptive impact of wrong decisions in an automated environment. A careful deployment process must be set up with different control points in segregated organizational areas. In the best cases, the development

Table 3.2 Costs and benefits of alternative development/maintenance sourcing

Process Task	Internal	Third party
Time to market	**low** Development time is longer on first scorecard, then through process of standardization and a stable team it reduces substantially (about 2 months to complete a full development, apart from data availability issues)	**low** Two/three months plus data extraction and certification
Data knowledge – business process link	**high** Focus and feedback on data quality processes.	**low** Self contained projects
Deployment complexity	**low** Deployment and operational process change is embedded in the development.	**medium** Specific effort required to integrate the scorecard in the operational processes.
Investment	**high** A plan for recruiting, training, and retaining specialists is needed. Additional investment in analytical software required (if not yet used for other processes, i.e., reporting, planning, …).	**medium/high** Related to consultancy fees; limited scalability
Specialist turnover	**high** Specific retention policies are required. Junior specialist to be added to the team, with slight overcapacity to address sudden exit.	**low** At least minimum continuity in knowledge of the bank's processes and data
Documentation	**high** Detailed knowledge of the business environment, reproducible results, and tailored documentation	**medium** Usually standardized delivery reports
Capacity	**high** Three member FTE team delivers five to eight scorecards per year.	**high** Some dependency with respect to the planning of external provider analysts

Process improvement	**high** Intensive data quality analysis and data interaction with process development contribute to high impact on many operational processes.	**low** Low attention to data / process interactions topics
Credit policy impacts	**high** Direct link to policy revisions and improvements	**low** Standardized deliverables
Cross-engagement on other analytical projects	**high** Scorecard developers can be engaged in other analytical projects.	**medium** Capability, capacity, knowledge, and costs issues

Source: Authors.

environment is coupled with the decision-support system that will implement the scorecards, giving more robust control mechanisms to the implementation activities.

Most of the previous issues can be managed by setting up a model of governance procedure. The model promotes self-documenting procedures and system-generated reports and analysis, and requires detailed explanatory program comments from developers and production of functional documentation, providing clear guidelines for reproducible results. The model defines comprehensive operational documentation regarding system implementation and operational controls to minimize misunderstandings and errors in the implementation of the process.

Models are growing in complexity because the business processes and policy rules that they incorporate, for both underwriting and pricing, are fairly complex. Moreover, dynamic and data-driven features are incorporated in models to take advantage of developments in data warehousing and to search for competitive advantage through better analytics (Davenport, 2007).

The recent financial crisis has revamped some credit factors that were undervalued – sometimes ignored, like the infamous “ninja” loans – in the previous growth cycle: affordability of financial liabilities, over-indebtedness risk, and the resilience (through liquid asset holdings) of the individual and the household. The search for a highly streamlined evaluation process and an excessive reliance on credit bureau scores without further insight into the asset and liabilities position of the applicant and his or her income perspectives has generated in many cases a very

vulnerable portfolio with respect to adverse changes in the economic environment. Household credit risk management has to reconsider the applicant's profiling information by giving more emphasis to debt ratios and long-term income generation capacity to evaluate the sustainability of household debt in adverse conditions and to avoid overextending credit to financially stressed individuals. Thus, there is again the need to collect and store more information on customers, especially on asset and liability values and types to be used for model development and policy definition. Banks with multiple relationships with customers can leverage existing data to incorporate them in the credit-decision processes. But those data are present in legacy systems that for various technical and operational reasons are not available for credit risk modeling and monitoring, and that makes the task of building them into the DWH expensive and time consuming.

Profitability measures should also be incorporated into evaluation processes, because banks are seeking profitable relationships, not risk minimization alone. For example, we can define a relatively basic revenue function (adapted from Finlay, 2006) as:

$$\Pi_i = Y_i - \sum_{k=0}^{n} \{\theta_k B_{ik}\} - \delta \tag{3.2}$$

where Y_i is the net interest and commissions paid by i customers during the outcome period of 12 months, B_{ik} is the balance in bucket $k, k = 0, 1, \ldots n$ past due, θ_k is the impairment coefficient in bucket k, and δ is an estimate of the cost of managing the account over the outcome period. This crude revenue estimate at the accounting level can be combined with the outcome of a traditional risk scorecard to enable the study of the joint rank order of the risk and revenue measures. A similar approach can be made by collecting the costs and revenues associated with each account, and calculating the net margin as the difference between revenues (interest plus fees) and costs (including expected loan loss) by score range, applying discounting if needed (see Table 3.3 for an example).

3.3.1 Individual models example: application risk scorecard

The best known individual model is the application risk scorecard, which encompass many of the complications and options faced by the analyst in a typical model development project. The aim of the model is

Table 3.3 Net margin by risk score

score range	# accts	£ out standing	insurance revenues	interest revenues	bad rate	LLR	impairment	other costs	net margin
300	7.481	3.200	176	534	50,0%	57,0%	1.824	267	-1.381
310	6.256	2.713	149	452	41,4%	46,5%	1.262	214	-874
320	5.604	2.772	152	458	33,3%	36,8%	1.020	186	-596
330	11.180	2.648	146	420	26,1%	28,7%	760	174	-368
340	12.607	2.794	154	467	20,0%	22,5%	629	168	-176
350	13.512	2.868	158	579	15,0%	16,1%	462	155	120
360	22.132	2.888	157	581	11,1%	12,4%	358	149	231
370	23.154	2.765	151	456	8,1%	8,6%	238	137	232
380	31.654	2.705	149	405	5,9%	6,2%	168	121	265
390	22.321	2.658	146	387	4,2%	4,2%	112	119	303
400	17.438	2.554	139	364	3,0%	3,0%	77	107	319
410	15.323	2.538	136	349	2,2%	2,1%	53	98	334
420	12.964	2.436	124	346	1,5%	1,4%	34	96	340
430	7.854	2.327	112	321	1,1%	1,0%	23	90	320
440	5.649	2.231	87	287	0,8%	0,6%	13	84	277
total	215.129	2.654	151	412	11,2%	13%	344	137	97

Source: Authors.

to find the best predictors of customer default by using all the available internal and external (credit bureaus) information gathered from a defined past time window, then using a performance time window to observe the customer's effective behavior. Data must be gathered from different sources and carefully validated. Many issues arise at this project phase: how to treat missing data and outliers, how to use continuous variables, if and how to class them by appropriate intervals and then solve problems with non-monotone (and possibly nonlinear) behavior,[5] how to spot high-order interactions between explanatory variables, and how to define target variables (binomial, multinomial, continuous) and tricky "indeterminate" areas. The appropriate split of the development sample between estimation, validation and control sub-samples must be performed to ensure that a sufficient number of bad accounts will be in each one to produce statistically significant results (or apply some bootstrapping techniques).

An effective estimation technique must then be applied. For example, a logistic regression could be applied, possibly avoid a stepwise variable selection (Harrell, 2001, p. 56–60). Other multivariate statistical analysis or data-mining techniques can be used to select explanatory variables and to perform validation at each stage by using appropriate measures (AUROC, Gini Index/Somer's D etc.). One of the trickiest problems arising from the application scorecard is how to treat the rejected

applications that are part of the population demanding credit in the observation time frame. In many cases, when rejected customers are a significant share of the total applications, they should be considered in the model development by assigning them a performance based on some kind of estimation. Otherwise significant biases are introduced into the estimate model (see Feelders (1999), Crook et al. (2004)). Whenever possible and economically viable, it is advisable to access credit bureaus to verify whether rejected applicants have received credit of a similar kind from other institutions at around the same time. Then the scorecard can evaluate the rejects based on their performance with those other lenders. The remaining population can be assigned to "bad" or "discarded", providing that the development sample is appropriately re-weighted.

At the end of the loop a final model can be selected and estimated and then validated on a control sub-sample. A scaled score is calculated, and the expected population distributions across scores are computed.

A further validation on recent data is advisable to assess the stability of the characteristic and score distributions of the most recent applications (over the previous 1–3 months) to spot any significant changes that could affect the scorecard performance.

In best practice, all the processes are subject to a detailed governance process where all the technical aspects are disclosed (that is, what estimation algorithm to use and why) and the execution steps are checked by a third party not involved in the development process. Depending on the size of the portfolio to which the model will be applied, a completely independent review might be required by a subject expert designated by the bank. The governance process needs to carefully balance the developer choices with mandatory steps to avoid an excessively mechanical approach to model development leading to suboptimal or even adverse outcomes.

3.3.2 Impact of models on credit and underwriting policies

The development process can highlight weaknesses or the need for the redesign of credit policies and operational processes. Change in the model's discrimination power and well-balanced credit characteristics embedded in the scorecard can reduce the referrals to mere underwriting activity, as in the case of the segmentation of more effective decision keys in the decision-support systems. In the case of adverse economic conditions, it can be advisable to broaden the scope of referrals and gather additional information to be manually assessed due

to the cost and implementation time for new models, or in the presence of deployed models that cannot ensure robustness under changing customer/economic conditions. Again, a comprehensive and detailed periodic monitoring process can help to spot deviations and population shifts, triggering suitable corrective actions.

3.4 Portfolio model framework

The other main area of model development and application is portfolio management, where aggregations of individual accounts, usually in time-series format (and for wider time spans), are used to assess, simulate and forecast economic events critical to the business; for example, new business development, prepayment dynamics, risk–reward structure, impairment forecast, the macroeconomic stress impact on risks and rewards, nonperforming loan recoveries, and many others. For some relevant events (for example, prepayment or vintage risk dynamics), these models can give additional useful information; this can drive management decisions that have significant impacts, especially on expected overall economic results. For instance, senior management does not expect the emergence of surprises without any previous evaluation of the risks in deviating from the expected path. In the case of deviations, management needs to know what managerial action can be considered to mitigate the adverse effects. In this context, risk–reward models are very effective in giving senior management the synthetic levers to assess the effect of pricing, risk appetites, product characteristics and customer profiles for the relevant economic measures.[6]

Again, the critical requirement is related to the availability, integrity and usability of the data. In a rapidly changing environment, mergers, acquisitions, changes in IT systems, accounting rules and breaks in historical recording of data can lead to discontinuities that result in a short time series that severely limit the applicability of many useful methods. For example, when using the vector autoregressive model or the vector error correction model (see Lütkepohl, 2005) to study the dynamic correlations between portfolio aggregate outcomes and macroeconomic values of interest, a time series of 60 to 120 months or more is required to cover different economic conditions and sufficient degrees of freedom in estimation.[7] But few banks have those long-term series readily available and consistently recorded. Any dynamic impulse response analysis that could give great insight into stress analysis and uncertainties evaluation cannot be performed using this very powerful approach.

Models based on vintages with indicators arranged in matrices where the time of the first event is in the rows and the historical development of any indicator is in the columns are less stringent in the time span needed to be developed and are widely used in estimation of some relevant aggregate values such as LGD (loss given default) or expected default frequency.[8] The assessment of the long-term macroeconomic impact on vintage dynamic structures is a little trickier and again requires a longer time series to be effectively performed.[9] Portfolio forecasting models are the tool we briefly delve into, given their common use for short-term forecasting and economic planning. In credit risk management the asset forecasting model for expected impairment estimation is widespread.

3.4.1 Portfolio models: impairment forecasting

Asset impairment is a critical process tightly regulated by laws, supervisory rules, credit risk management's best practice challenges and close scrutiny by senior management. Its disclosure is one of the main indicators of the effectiveness of credit risk management, and its value is a significant component of the cost side of the P&L of the bank. It is a measure tightly linked with the expected loss of booked loans and also, although indirectly, with the capital that the bank has to hold to comply with regulations and safe business running.

An accurate impairment forecast is central to the planning process of the financial institution. This forecast can be carried out using a set of models devoted to asset distribution projections for performing loans – both the current and delinquency book classified by the bucket of arrears and of the nonperforming book – usually charged off the books with different specifications by country. Along with the asset distribution, other models are devoted to estimating the risk parameters associated with each aggregated asset classification, in particular PDs and LGDs. These are not strictly speaking the well known Basel II parameters, because the requirements of the International Financial Reporting Standards (IFRS) on impairment do not allow the expected loss approach.[10] The impairment calculation is based on the roll-rate approach where the percentage of assets that move from the initial delinquency to default is derived from frequency ratios based on short-term historical experience. The impairment allowance in the retail portfolios is mainly assessed on a collective basis and is based on the drawn balances adjusted to take into account the likelihood of the customer defaulting (PD_{pit}) and the amount estimated as not recoverable (LGD). The basic calculation for bucket i is as

follows:

$$\textit{Impairment allowance (i)} = \textit{asset amount (i)} \bullet PD_{pit}(i) \bullet LGD \qquad (3.3)$$

The $PD_{pit}(i)$ increases with i, the number of contractual payments missed (also known as the bucket classification), thus raising the associated impairment requirement.

Unidentified impairment allowances are also raised to cover losses which are judged to be incurred but not yet specifically identified in customer exposures at the balance sheet date and which, therefore, have not been specifically reported.

The roll-rate model is the most common tool for asset distribution forecasting and risk parameter estimation in which the extrapolation of value in bucket i at time t is:

$$a(i)_t = r_i \cdot a(i-1)_{t-1}, \quad r_i = \frac{a(i)_t}{a(i-1)_{t-1}} \qquad (3.4)$$

Knowledge of the future value of the total receivables[11] and the use of an extrapolation of historical roll rates allow the short-term forecast of the asset distribution and the expected charge-off.

Roll rates are then used to estimate the risk parameters. For the identified impairment, the value of the account moved to charge-off is averaged with respect to the average value of the bucket for a set time window. For the unidentified impairment, the incurred but not yet reported calculation is based on the probability of the asset moving from the performing portfolio (bucket 0) to being specifically identified as impaired (bucket 1...n) within the given emergence period. The impairment is calculated in the same way as a ratio of observed values for a specific time window, and from then on it goes to default.

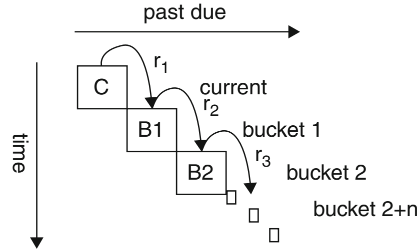

Figure 3.1 Roll-rate exemplification
Source: adapted from Breeden (2010)

A slightly more complex approach is applicable to the task, namely the Markov chain model. One of the drawbacks to the roll-rate scheme is the fact that it does not consider the movements of the accounts up and down the buckets due to partial payments.

In the Markov approach, a transition matrix is developed that takes into account all the states of the loan and estimates the probability of transition between states using a statistical estimation technique or a certain average of historical value for a defined time window. One drawback of the approach is that the risk that the accounts classified in each state are not homogeneous, determining time dependence between states and probably giving biased or inconsistent estimates.

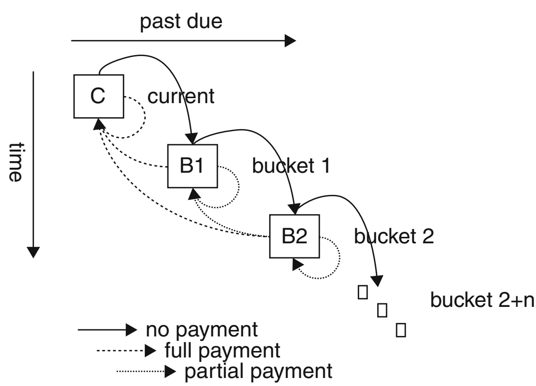

Figure 3.2 Markov chain exemplification
Source: adapted from Breeden (2010)

Table 3.4 One month Markov matrix

	t+1					
t	0	1	2	3	4	n
0	99,37%	0,63%	0,00%	0,00%	0,00%	...
1	36,80%	32,56%	30,64%	0,00%	0,00%	...
2	9,68%	12,64%	27,76%	49,93%	0,00%	...
3	6,95%	6,28%	9,40%	24,42%	52,95%	...
4	6,87%	2,49%	2,04%	7,49%	22,89%	...
n	...	...	...	...	...	...

Source: Authors.

3.5 Conclusions

The financial crisis we have experienced in recent years has put under scrutiny the credit risk management tools that have been developed and used in the last decades. While they have performed well in times of economic booms and even in mild recessionary times, they have shown weaknesses by giving inadequate evaluations of risk dynamics under severe stress, casting doubt on the whole credit risk profession and toolbox. The main lessons learned, in our view, are related to an increased awareness of data quality and of the wider scope needed to control for the sustainability of customer obligations. Another lesson is the rise in the knowledge of the macro-variables that impact customer and portfolio performances, enabling awareness of whether the expected impacts on economic measures coming from stressed economic conditions can be disruptive for the long-term sustainability of a business. Research into new, more powerful data analysis tools should be unceasing.

Notes

1. A brief historical account, albeit a little hagiographic, is booklet FIC50, issued on the 50th anniversary of a well known company specializing in decision-making tools. From a sociological (critical) perspective, see Marron (2009), Chs. 7 and 9. An account from a leading player is Rosenberger (2009), Ch. 1.
2. With this concept we characterize models whose operational application affects the performance of the customer in the short term, determining a sudden change in behavior that affects the model's performance in a typical feedback loop.
3. See Table 3.1.
4. This is a central concept in modern risk management toolbox: for more insights see Taylor (2007), esp. Ch.7.
5. For example, middle-aged applicants are riskier than younger applicants, but older are less risky than middle-aged and younger: how this can be interpreted, and is it compliant with regulation if incorporated as is in models?
6. For more insights see Chapter 10 in this volume.
7. See, for example, Crook and Banasik (2012) for an exercise at the aggregate level.
8. Originally proposed by actuaries, see England and Verrall (2002), vintage models are used for LGD estimation, see Chapter 5 in this volume.
9. See Breeden (2010), especially p. 220 and Chapter 6 onwards.
10. Under IFRS, the literal interpretation of impairment allowances are where there is objective evidence of impairment as a result of one or more loss events that have occurred after the initial recognition, and where these events have had an impact on the estimated future cash flows of the financial asset or portfolio of financial assets. For collective assessment, the principal trigger point for impairment is the missing of a contractual payment (any missing

payment at the contractual due date) defined by credit policy consistently adopted across all credit cards, unsecured loans, mortgages and other retail lending. The impairment value is recorded as a cost in the current P&L.
11. A set of vintage roll-rate models might overcome this simplification, but at the cost of greater complexity in the model management.

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4
SMEs: Credit Risk Modeling

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4.1 Introduction

In this chapter we discuss credit risk modeling with particular respect to the small–medium enterprise (SME) segment. After a brief introduction to the meaning and the purposes of an internal rating system, the first part introduces the main differences between internal rating models (that is, bank systems) and external rating models (external agency systems). Given the aims of this chapter, we will concentrate more on bank models explaining the different types of internal systems, the related parameters and the regulation issues.

After this preliminary explanation we will focus on the main components of an SME credit risk model according to the experience of a major Italian bank and the most recognized techniques at international level. Specifically, the availability and the quality of information will be underlined and the various sources of data will be discussed (customer records, qualitative data, financial data, internal information, public information and private information). The different approaches to the integration of datasets will be introduced and we will demonstrate how to arrive at a score and a default probability (DP) that represent the risk contribution of a customer with respect to the whole portfolio. A brief explanation about how the final information is managed in a bank (downgrading or override processes) will complete this part.

In the last section of the chapter we will focus on the way banks' risk managers use internal rating, and its implications in credit management. This concept is highly significant because it shows how these models reflect on the daily life of people and corporates. The difference between price-setter and price-maker banks will be introduced, and consequently the main formulas and policies for loan rates and loan

returns will be explained. Finally some suggestions about internal capital allocation strategies will be given showing that capital allocation follows a value creation rule. The two processes for capital allocation and their principal steps linked to reliable internal rating systems will be summarized.

4.2 Internal and external rating systems

A credit rating represents a synthetic opinion about the debtor's capacity and willingness to fulfill its obligations at maturity. The rating gives an estimate of the default probability based on the subjective analysis made by a bank or rating agency.

Since 1990, the relevance of rating systems has increased, together with the importance of rating agencies. Such agencies (Standard & Poor's, Moody's, and Fitch) play an important role in determining the risk and return of bonds, with important implication for the issuers' cost of debt. Similarly, internal rating systems assess the riskiness of a bank's customer and thus define an adequate interest rate for a loan (especially after the introduction of Basel II Principles in 2004).

Internal and external rating systems have several differences with respect to both the logic and the parameters used for the risk assessment. It is important to analyze these differences in order to understand the mechanism of the corporate risk model. Three main issues should be considered: counterparts, availability of information, and incentive systems.

Regarding the counterparts, the role of rating agencies is that of delegated monitoring. The targets of their valuation are bond issuers such as governments, banks, and corporations. Bond investors benefit from the consequent reduction in information asymmetry. Instead, banks' rating targets are customers who require credit. Basically they are corporations distinguished by total assets: Large Corporate (total assets higher than 250 million), Corporate (up to 250 million), SME Corporate (up to 50 million), and Small Business (up to 5 million).

Regarding availability of information, an important point is that banks' customers are not comparable to rating agencies' targets, which usually show publicly available information from financial markets (such as stock price and bond spread).

Conversely, banks have privileged access to their customers' private information, such as movements in their deposit accounts. Moreover, banks have access to the information provided both by the public

Credit Bureau (Bank of Italy) and the private Credit Bureau for foreign customers.

The third issue is related to incentives. The goal of rating agencies is to provide an independent opinion based on widely known and approved criteria. The reputations of rating agencies (measured in terms of good and reliable forecasts) is the most important asset for them to survive in the market. A revision of a precedent rating could damage their reputation, so they try to issue as stable a rating opinion as possible; that is why rating agencies usually perform a "through-the-cycle" approach in their models. This approach implies a lower than merited credit rating when the economy is booming to take into account the issuers' risk worsening in recession, and a higher than merited credit rating during recessions to take into account an improvement in issuers' risk in economic expansion. Therefore, ratings provided by the agencies can be considered a market-adjusted, default probability valuation relative to the economic cycle.

Internal rating systems have different objectives. Banks are both providers and users of their own valuations; therefore, they are interested in preserving their credit quality rather than their reputation. Internal ratings should be more up to date than external ratings, and should react more quickly to changes in customers' economic conditions. The rating stability is unimportant because internal systems should have the ability to quickly signal any worsening of the customer's economic condition. This method is called "point-in-time" and, unlike external rating systems, provides information with limited temporal usage.

4.3 External or agency rating

Rating agencies release not only an opinion but also an outlook on the economic condition of the counterpart. Within the outlook there is also the probability of an agency making a revision in the future. A "credit watch" indication means that newly available information is under the agency's scrutiny that can modify the opinion in the near future.

The process for the first rating opinion can take weeks or months because of the need to collect all the relevant information available about the company. Again, differently from internal rating, this opinion reflects an entirely subjective valuation process. It is not possible to quantify an agency's rating opinion. Agencies use a homogeneous classification process; in fact, the final classification results in an ordinal scale that divides debtors into different classes from investment grade (the

lowest risk class) to speculative grade (those with highest risk but also the highest returns). Only ex post is it possible to assign a cardinal value to default risk through the time-series observation of the defaults of the companies in each class.

The process of assigning a rating follows a number of discrete steps. First, the analyst team produces a draft report with the main issues concerning the debtor. Second, a special committee releases a final report that contains the rating opinion. The valuation process is based on two aspects: *business risk* and *financial risk*. Business risk is related to the industry sector of the issuer. The valuation process takes into account the industry sector's growth perspectives, its degree of competition, the portfolio of products or services offered by the company, its management ability, and its strategic process and development projects. Financial risk involves the balance sheet data and the budget analysis with projections about future cash flows and the applicant's ability to meet financial obligations. Standard financial indicators are computed and compared to those from other companies in a peer-to-peer process to make the valuation process as homogeneous as possible. The final rating is the result of a joint valuation of both business conditions and the financial situation in a stress test analysis (under the demand decrease hypothesis, or increasing the cost of debt, or losing operational efficiency). Once all the information received has been analyzed and approved, the committee then releases a final opinion on the company's rating.

In summary, in contrast to the internal rating, the main characteristics of an external or agency rating are related to the stability and the adjudged goal.

4.4 Internal or bank rating

Internal ratings represent, like those from an agency, a synthetic opinion about debtors' ability to meet their obligations at maturity. Basel II (2004) regulation assigns a key role to internal rating systems to make banking capital allocation much more risk sensitive. Within such a framework, a relevant feature is the so-called Pillar 1 (heavily modified with respect to the previous Basel I Accord): credits related to a single category of customers (that is, private companies) require regulatory capital calculated according to their specific riskiness and valuated through internal rating systems (IRB – Internal Rating Based). Banks can use the internal rating approach upon the approval of the banking authority and are responsible for the risk estimate they give to each single debtor and for the

whole portfolio. Basel II indicates six drivers to estimate losses given the probability of default:

1. the one-year default probability (PD);
2. the loss given default (LGD, inclusive of the costs of credit recovery and the opportunity cost);
3. the exposure at default (EAD), which is a measure of the customer exposure at default;
4. the maturity of the contract, which increases the probability of downgrading;
5. the diversification of the credit portfolio (that is, few loans of considerable size or many loans with small exposure); and
6. the debtors' correlation, which depends on the diversification of the portfolio.

Factors from 1 to 4 should be carefully measured by an internal rating system. According to the degree of sophistication of the internal rating systems, banks are allowed to choose between a basic or an advanced approach. The first is called FIRB (Foundation Internal Rating Based) that allows the banks to compute only the PD estimate from their internal systems while the other factors are provided by the banking authority. The second approach is AIRB (Advanced Internal Rating Based) that allows banks to internally compute all the factors. Internal rating systems can be used to compute the minimum capital requirement only on approval by the banking authority, which is obtained after the demonstration of the ability of the internal rating classification. Internal PD, LGD, and EAD model predictions are compared to the time series of the banking authority in order to measure the forecasting accuracy of the internal systems. Once this check is passed, the bank can use the internal rating model only if it is involved in the entire credit allocation process, from loan issues to credit risk monitoring and pricing.

How do banks develop internal rating models? What are the data sources used in the process?

Along common guidelines suggested by the banking authority, each bank develops its own model. Important differences among the models are related to data sources and treatment, the indicators to compute, the variables to include in the shortlist, the correlation model between dependent and independent variables, the caliber function adopted to convert the score rating into the PD, and the number of rating classes. The banking authority only establishes a common definition related to

the default status, which is the starting point for estimating the PD, LGD and EAD parameters.

4.4.1 Information for internal rating

Italian banks have reliable knowledge about their customers through both public and private information. In fact, banks can analyze their customers through publicly available data such as balance sheet accounts and related financial indicators. They can also use privileged qualitative information, such as the degree of market competition or management quality, thanks to the close relationship between network managers and their customers.

A static internal rating about bank customers is formed by standardized (annual) reports. In fact, this information (both financial and qualitative) tends to be stable over time, offering the possibility of stable valuations that thus define stable asset pricing or homogeneous capital allocations. Commercial relations are not stressed by rating fluctuations, and top management and banking authority communications benefit from this stability. But this static internal rating fails to signal sharp changes in customer behaviour. The probability of losing market shares is high when competitors (other banks) use much more reactive rating systems.

4.4.2 Customer records

All public information about customers (location, year of foundation and business sector) and related shareholders (age, role and tenure) are collected in the customer record. Shareholder information is particularly important for SMEs because the personal risk profile is much more closely connected to the riskiness of small firms.

4.4.3 Qualitative information

All information available on business, market share, market competition and management ability is collected for the qualitative information of a bank customer. The more a bank invests in qualitative data collection, the higher the predictive ability of the internal rating. In fact, the role of qualitative information is often undervalued, even if "relevant qualitative information can improve banks' effort in reaching a complete information set upon which to establish an accurate counterpart valuation" (Bank of Italy, Circolare n. 263, December 2006).

Qualitative information is very important for big companies. In fact, the greater complexity of big corporations diminishes the predictive role of quantitative information. While internal rating can rather exclusively focus on quantitative information for SMEs, on the other extreme it is

focused only on qualitative information for multinational corporations, governments, and banks. Moreover, qualitative information is important in two more processes: the valuation of new companies; and the valuation of joint ventures related to a single business, a business sector, or a geographical area.

In the case of a new company startup – a riskier proposition than that of a mature company – the ability required for the internal rating is to follow not only quantitative information (perforce scanty in a startup) but also the qualitative information about the firm's projects and its management. In case of joint ventures, the lack of historical data can be compensated by qualitative data about the strategic plan of the business or about the companies that participate to the deal.

4.4.4 Financial information

All information related to the balance sheet account and related financial indicators (i.e. cash flows, leverage liquidity, and investments) are collected for financial information. As with qualitative information, financial information is very important for big corporations. In fact, financial indicators and their trends (computed for different time horizons) can give important information about the economic health status of a company and can also predict the future firms' solvency capacity. The relation between a bank and its customer is an important source of this information, together with the relation between the customer and the banking system. The integration of both information sources represents the basic data source for the company's risk profile for a dynamic internal rating system. The combination of different data reports (usually monthly reports) is highly variable. This information set (internal trend, external trend, or external private trend) is very dynamic and allows rapid signaling of possible customer misbehavior. Internal ratings based mainly on trend information allow the immediate reflection of the variations in customer relations with the bank or the banking system, and this gives the bank an important competitive advantage in the management of customers (that is, the ability to prevent default losses through more accurate credit risk measures).

In contrast, a dynamic internal rating system can be unstable and can increase fluctuations in customer valuations. It can be difficult to explain a valuation change both to the external stakeholders (how to explain a loan re-pricing because of a deteriorated credit rating, or how to explain a capital requirement fluctuation to the banking authority) and to internal stakeholders (that is, risk provisions or value reinstatements are not desirable).

Internal information

We can define internal information as the data concerning the customer's financial relation with the bank. This information consists of the kind of loan held by the customer, the probability of default or delay in payments, and, in general, each kind of behaviour, whether positive or negative. There is a trade-off between the reactivity and stability of the internal rating systems: the faster the reaction to new information, the less stable the system. From this perspective, a system based on high frequency (or monthly) data is useful. Otherwise, overweighting the related information trend might be better.

Public information

Public information comes from the credit bureau of the banking authority. The database is managed by the surveillance authority with the aim of an efficient distribution of publicly available information about the banking system. The feed mechanism of the database is built from a mandatory base, because banks must deliver information about their counterparts. But banks receive reports containing information about the relations of their customers with the whole banking system. To attain this objective, each financial intermediary must provide monthly information about the customers' risk, normally by the 25th day of the following month. The feedback report delivered to the banks has a two-month lag.

The information is split into five categories (cash loans, endorsement loans, collaterals, financial derivatives, and personal data). Public information is an important source for big customers. Because delivering information only for significant movements is mandatory, the Credit Bureau of the Authority has information only about the most important customers with several accounts (SME corporate or corporate); thus the probability of accessing information about small businesses via this means is very low.

Private information

Private credit bureaus can release information about the relation between a customer and the banking system. They cannot rely on a mandatory feed system to update their database, however, as does the authority's credit bureau. They collect data even for small movements and for all contracts. Private credit bureaus use different risk categories with respect to the nature of the relation (credit card, fixed loans and so on), which complement the information from the authority's credit bureau for the small business segment. The probability of finding retail or small business

customer data in private credit bureaus is higher than in the authority's bureau.

Data source integration and DP computing

All information datasets can be managed and integrated in several ways: through a logistic regression or through a weighted risk correlation. Risk is the default probability (DP), and represents the event to be measured or forecast through statistical tools (univariate analysis). The final valuation is generally related to the integration of different datasets with the default event (multivariate analysis). The final result is a score that represents the risk contribution of that customer with respect to the whole portfolio. All these scores, within different risk categories, are used as a proxy for the DP. There are three ways to implement this process. The first, and the most common in the banking system, assigns a PD through a calibration tool (a Bayesian tool) that uses scores obtained in a representative time series, usually a single economic cycle. A second approach projects the past insolvency rate as an estimate of the PD within each risk category. This approach is common among rating agencies. The third approach is called "mapping" and links internal rating systems to those from rating agencies, such as Moody's or Standard & Poor's. Different scales are made homogeneous in order to translate the rating from the agencies as an internal PD.

Override

The customer rating is obtained through data collection and manipulation. This result shows an accuracy level that can be measured in a scale from zero to 100% (through accuracy ratio test or Gini index). Even considering a higher volatility for different portfolios or different stages of the process, a 70% accuracy ratio is considered a very good result for a model. The model is not able to forecast customer solvency because of limitations in both the data (few banks hold reliable long-term databases) and the model. In fact, a model can be inefficient because of the errors in data management or because of the inherent errors in a mathematical model that cannot take into account all the randomness (macroeconomic scenarios, business development plan, merging plan, and price sensitive news).

It is very important to have downgrading or override processes for the ratings.

In case of unreliable information, banks have rules to force ratings: downgrading rules implies a deterioration in the rating condition (when there is no up-to-date financial information or a very old dataset). In this

situation, the conservative policy is to downgrade the customer rather than to retain the same grading position. The opposite happens when a model fails to consider risk-sensitive information. The override is a procedure to correct the rating (deterioration or amelioration). Experts at the banks are able to check the rating adequacy for each customer; these experts can modify ratings on a judgmental basis that is motivated because of the failures of the rating model. The override guarantees that every relevant aspect of the customer is considered in the rating.

The importance of information both for the bank and for the customer

In Document 263, the Bank of Italy states that complete information is very important.

But let us suppose that a legal reform were to be enacted to enforce registration of customers in both the public and private credit bureaus; and what if that reform cancelled the information about customers that fulfilled their obligations? This reform might be advantageous to those customers with past insolvencies. The reform would create a bias in the internal rating systems because of the lack of the information about the past. Thus, this bias would allow banks to extend credit once again to such customers. Figure 4.1 shows the potential impact of such reform.

Simulation of bureau score (after reform)		
Score class	**% Pop.**	**% Bad Rate**
1	5	90
2	5	65
3	10	23
4	10	14
5	17	11
6	17	7
7	10	7
8	10	5
9	8	3
10	8	2

Bureau score (pre-reform)		
Score class	**% Pop.**	**% Bad Rate**
1	1	77
2	7	55
3	2	28
4	1	14
5	89	7

Bureau score (pre-reform)		
Score class	**% Population**	**% Bad Rate**
1	0	71
2	3	46
3	2	27
4	1	12
5	1	10
6	92	5

Figure 4.1 Simulation of bureau score

	A	B
Rate insolute	0	5
Amount insolute current	0 €	0 €

	Situation Pre-reform		Situation Post-reform	
	A	B	A	B
Score	477	390	471	473
Rating class	6	1	5	5
Risk (in terms of Bad Rate) associated to the corresponding rating class	7%	90%	11%	11%

Figure 4.2 Example of treatment of two customers (A and B) with and without reform

The customers ranked at 5 with a bad rate of 11%, might have different risk degrees. As an example, consider two customers, A and B, whose riskiness is measured pre- and post-reform.

Clearly B, with insolvency in the past, would be financed by A. In fact, the bad rate computed after the law reform would be the same (11%), because it would not be possible to distinguish A from B. So, the two customers being ranked the same (5), the pricing would be the same for both.

With a complete set of information, however, it would be possible to distinguish B (rank 1) as 13 times riskier than A (rank 6) and apply different pricing conditions for both.

4.5 Risk management and rating

We focus on the way internal rating is used by banks' risk managers and its implications in credit management.

Rating assignments and updating processes are related both to loan allocations and monitoring.

Loan granting implies rating assignment and customer data entry. Once these inputs are introduced, the system computes rating scores that should be updated through the input from data monitoring and management. When a loan is refunded, banks usually revise the rating score

on the basis of new information (such as a new balance sheet account, or new customer data). The accuracy of the rating is the responsibility of the customer manager, who is in charge of keeping customer data updated and must perform the monitoring activity. The internal committee is also involved in determining customer credit ratings in cases of loan refunding. According to different models and needs, during this process it is also possible to apply downgrading or override rules on the basis of new and relevant information.

What are the main outputs of a rating system? Reasonably, we might apply the general rule of asset pricing, that is, the risk and return should be related: the higher the risk, the higher the interest rate required.

In loan pricing we also can take into consideration banks that are price setters or price takers. Price setters are those banks working in an inelastic market that have great enough contractual power to settle a price; price takers are those banks that follow market rates, and it is very important for them to measure loan returns.

Banks should find an equilibrium rate to make sound financial decisions with respect to three kinds of costs: (1) borrowing costs, (2) expected loss costs, and (3) risk capital allocation costs.

Borrowing costs are usually expressed in terms either of the risk-free rate or the internal pass-on rate (POR is a rate that remunerates banks' collecting subsidiaries and assigns an equilibrium cost of funding for banks' investing subsidiaries).

The costs from the expected loss represent a key concept for understanding banks' risk-neutral rating systems. In fact, the concept relates both to DP and LGD and needs an efficient rating system that determines these two parameters.

The cost of the risk capital allocation is related to the bank's own capital that should be put aside to balance unexpected losses. This cost is determined by the financial market conditions or the ROE that managers want to reach as a target for shareholders' remuneration.

Equilibrium rate r is computed by summing up the three cost components and considering an exposition EAD ($EAD = 1$) and a value at risk (IVaR) given by the following formula:

$$r = \frac{i + PD^{*}LGD + IVaR^{*}(K_e - i)}{1 - PD^{*}LGD}$$

where the risk-free rate i (POR in the case of pass-on rate) is the borrowing cost; $PD^{*}\ LGD$ is the expected loss cost; and $IVaR^{*}(K_e - i)$ is the risk capital allocation cost.

This equation shows what the impact of the rating is on the pricing and how important the impact is in determining bank profitability.

In case of a price-taker bank, we focus on market loan returns. In this situation, rates are set by the market, and the bank is restricted to deciding whether or not it is expedient to grant a loan at the relevant rate. Internal rating systems play an important role by accurately assigning a rating score, which represents the key information for loan granting. The return on risk-adjusted capital (RORAC) could be a good indicator and is computed thus:

$$RORAC = \frac{r^*(1 - PD^*LGD) - TIT - PD^*LGD}{IVaR}$$

The numerator represents the market return adjusted by expected loss and cost of funding, while the denominator is the loan-related portion of capital at risk. When RORAC is higher than the minimal target return (K_e – TIT), it is expedient for a bank to grant a loan.

$$\left\{ \begin{array}{l} RORAC > (K_e - TIT) \rightarrow grant\ \ a\ \ loan \\ RORAC < (K_e - TIT) \rightarrow do\ \ not\ \ grant\ \ a\ \ loan \end{array} \right\}$$

The loan-granting process depends on size and riskiness. The greater the size or risk, the higher the level within the bank at which the decision

Rating	Weight	Description
R1	0.40	Minimum risk
R2	0.50	Low risk
R3	0.60	...
R4	0.70	...
R5	0.80	...
R6	0.90	...
R7	1.00	Medium risk
R8	2.50	...
R9	5.00	...
R10	10.00	Elevated risk
R11	15.00	Maximum risk

Loan	Rating	Weight	Weighted loan	Decision level
€ 500,000	R1	0.4	€ 200,000	Branch
	R7	1	€ 500,000	Regional
	R11	15	€ 7,500,000	Headquarter

Figure 4.3 Loan-granting process

is taken. The PD and RWA rating systems are related to the managerial level. At the lowest level (the subsidiary), a loan could be granted with a minor impact in terms of the DP, PA, or RWA. Each rating is associated with a weight according to its risk covariance with the portfolio.

This weight implies the definition of loan size and the level of the managerial granting process.

In the following table, an R7 (weight = 1) of 500,000 for a required loan could be granted locally by a subsidiary (200,000 granted) at the regional level in class 7 or 11 (7,500,000 granted).

4.6 Capital allocation strategy is another way of using internal rating models

Bank management should first allocate capital to the operative business units that can invest in profitable projects according the risk–return relation. Capital allocation follows a value creation rule.

This can be bottom-up or top-down. In the bottom-up rule, risk is related to the single position and then aggregated at the business-unit level, whose profitability is compared with the whole bank. In the top-down process, first the bank's propensity for risk is defined, then it is valued to determine the profitability of the business unit for capital allocation.

The process can be split into three steps: (1) computation of capital at risk, checking the regulatory requirements; (2) computation of risk-adjusted profitability (for a single position or the business unit); and (3) definition of capital allocation among business units.

Banks can develop successful strategies if accurate and reliable internal rating systems are available.

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5
The Critical Model Parameter: LGD

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5.1 Introduction

Chapter 5 discusses the definition, relevance, and application of loss given default (LGD) to credit risk management, as well as possible estimation approaches. LGD is one of the main parameters, along with probability of default (PD) and exposure at default (EAD), of estimations for both the Basel II regulation and economic capital reporting purposes. LGD estimates are also crucial for the determination of impairment allowances according to the International Accounting Standards (IAS 39) framework. However, LGD's importance should not be restricted to compliance requirements only, but should also be extended to business' best practice in the measurement and optimization of collection and recovery processes. In fact, starting with credit origination, the correct estimation of a financial institution's capability in recovery actions supports proper acceptance policies in terms of risk appetite and prices based on the risk profile. In such a context, severity models applied to open-default cases can suggest appropriate collection and recovery strategies that can lead to corrective actions on current criteria and the fine tuning of costs and resources.

The objective of this chapter is to fully explore the LGD estimation process and to provide tools for measuring LGD for various portfolios and products.

5.2 Overview of LGD

This section introduces LGD and gives an overview of the main issues related to its estimation.

5.2.1 Definition and calculation

Loss given default is the estimate of the losses that the Bank will face in case of customer or facility default. "In general, LGD is the loss, expressed as a percentage of the EAD, on a credit facility if the credit defaults." (BCBS, 2005b) In explicit estimation methods, the LGD is estimated for each facility in a portfolio using a reference data set (RDS) of defaulted contracts as the estimation sample. The objective is to determine the realized LGD for each facility in the RDS and then assign an LGD value to each non-defaulted facility. An important distinction is that economic loss is not the same as accounting loss: "The definition of loss used in estimating LGD is economic loss. (…) This must include material discount effects and material direct and indirect costs associated with collecting on the exposure." (BCBS, 2005b) For the purposes of retail credit risk measurement, the workout approach is the most accurate and widely used in practice. Workout methods evaluate the loss associated with a defaulted facility by discounting the cash flows, which include costs that result from the workout from the date of default to the end of the recovery process. The loss is then measured as a percentage of the EAD. The timing of cash flows and both method and rate of discount are crucial in this approach. There are four main issues arising when using the workout approach to compute the loss of a defaulted facility: (1) the importance of using the appropriate discount rate, (2) different possibilities about how to treat zero or negative LGD observations in the reference dataset, (3) the complexity of the measurement and allocation of workout costs, and (4) how to clearly define the completion of a workout. This chapter addresses these issues.

On the measurement side, the LGD is usually calculated as one minus the recovery rate (RR), defined as the discounted (at default date) value of recoveries received net of material direct and indirect costs associated with collecting on the exposure and divided by the amount of EAD. In formula, this measurement is:

$$LGD = 1 - RR = 1 - \frac{\sum_t C_t \delta_t}{EAD} \tag{5.1}$$

where C_t is the net cash flow at time t that comprises both positive flows received under contract from the borrower or through asset sales and negative cash flows that arise from internal and external costs. Each C_t is discounted at the time of default by a proper discounting interest rate δ_t given by a risk-free rate plus a premium.

The basis of LGD estimates is defaulted facilities. While the PD provides the likelihood that a certain counterparty (or facility) will default in a prefixed time horizon (for example, 12 months for Basel requirements), the LGD parameter provides the estimate of possible losses when the default actually occurs. Modeling approaches are therefore different from those used for PD, as are the construction of their samples. As mentioned above, the preference is to estimate recovery rates rather than loss rates, because LGD estimates must incorporate the discount factor arising from the time required to recover the due amount. Moreover, as a requirement in Basel II and in accordance with best practice and business adherence, LGD should be estimated at a facility level rather than at a customer level.

5.2.2 Basel II versus the IAS 39 framework

According to Basel II requirements for the Internal Rating Based (IRB) approach to retail exposures, banks that wish to adopt internal rating systems for regulatory and economic capital calculation must have internal estimates of LGD. Estimates need to be determined appropriately and applied to each exposure based on robust data and proper analyses that must be validated internally and externally. The LGD values must be differentiated on the basis of a wider set of transaction and customer characteristics (such as product type and collaterals) and need to be a conservative view of long-run averages.

The extension of LGD estimates derived for the purposes of Basel II to an impairment framework is allowable and considered acceptable, but with proper adjustments to meet IAS 39 requirements that mainly relate to the downturn effect, discounting effect, and inclusion of costs.

Downturn LGD

Under the Basel II framework, banks are required to add a downturn effect to LGD estimates to reflect losses that can occur during a downturn in the business cycle. The Basel Committee on Banking Supervision (BCBS, 2005a) provides guidelines for interpreting the meaning and definition of downturn LGD:

Paragraph 468 of the Framework Document requires that the LGD parameters used in Pillar 1 capital calculations must reflect economic downturn conditions where necessary to capture the relevant risks. The purpose of this requirement is to ensure that LGD parameters will embed forward-looking forecasts of recovery rates on exposures that default

during conditions where credit losses are expected to be substantially higher than average.

The ways to estimate the downturn effect and how to identify the downturn cycle might vary for different financial institutions and according to each regulator's guidelines. For example, the downturn scenario can be determined on the basis of the negative growth of GDP or a depreciation of residential properties larger than 40 percent. However, the BCBS paper suggests that the main principles should be followed in defining downturn scenarios.

Appropriate downturn conditions might be characterized, for example, by the following: for a well diversified wholesale portfolio, periods of negative GDP growth and elevated unemployment rates; periods in which observed historical default rates have been high for exposures that are representative of the bank's current portfolio; and for exposure where common risk drivers (such as collateral values) influence the default rates and the recovery rates, periods where those drivers are expected to be distressed.

Calculation of LGD and inclusion of the downturn effect is still a challenge for modelers. Recovery processes can last several years, and the final LGD can only be calculated when all information is available. This is true in particular for lengthy recovery processes like mortgage legal processes for house sales or repossessions. The first consequence of these recoveries is the lack of internal historical data (especially when inclusion of a downturn period is required) and therefore difficulty in ensuring robust estimates. In some cases, when downturn data is lacking, institutions can choose to add conservative buffers or stress some of the variables entering into the LGD model. These buffers and variables can incorporate a possible downturn effect to obtain a potential LGD increase in case of macroeconomic deterioration.

Discount rate

The Basel II framework discusses the specific treatment of the discount rate applied to the LGD estimation. "For the estimation of LGDs, measures of recovery rates should reflect the costs of holding defaulted assets over the workout period, including an appropriate risk premium" (BCBS, 2005a). In particular, the committee requires that cash flows relative to costs or recoveries are discounted according to an interest rate that is coherent with an investment with the following features: the amount is equal to the EAD of the loan; the time horizon of the investment is of the same length as the recovery process of the loan; and the risk of

a nondiversified portfolio is covered by a proper spread to be added to the risk-free rate. The committee does not provide suggestions on the method that should be used to determine the discount rate, but the method should reflect the cost of keeping the defaulted asset, as well as incorporating an adequate risk premium. Hence, the interest rate used to discount LGD cash flows should incorporate both the money value of time (risk-free component) and the risk embedded in the volatility of recovery flows (spread).

On the other hand, IAS 39 requires that the cash flows are discounted at the effective interest rate.

Costs

The definition of loss used in estimating LGD is that of economic loss. This definition means that estimates need to include a material discount effect and a quantification of direct and indirect costs faced by the bank when collecting the defaulted exposure. Another element of the workout's loss formula is the total discounted value of workout costs that, in theory, should comprise both direct and indirect costs registered during the workout process of the asset. The measurement of these costs can be a very difficult task. Direct costs are those associated to a particular asset (for example a fee for collateral appraisal); indirect costs are those required to carry out the recovery process but not directly associated with individual facilities (such as overheads for the workout department's office space). The assumptions about how indirect costs are allocated to individual assets will affect the final estimate of the workout LGD. In practice, assigning direct costs to defaulted facilities is not easy, and assigning indirect costs is even more difficult. One possible approach to overcoming these difficulties is to identify the key recovery costs for each product and to model them. The model uses a sample of facilities whose true costs are known, and allocates these costs from recoveries to the current default. Despite such difficulties, a bank that chooses to calculate realized LGD using the workout method must include all of the costs, both direct and indirect.

The IAS 39 framework, however, requires that legal costs related to the recovery process, as well as indirect costs, should not be included, to avoid double counting.

5.2.3 Cure rate/danger rate

One of the significant challenges that the modeler faces when developing an LGD model is the fact that the default definition might vary across institutions, and also between Basel II requirements and bank best

practice. This variation often creates a necessity to define so-called cure rates, or percentages of defaults without losses, that allows for embedding all kinds of default definitions in the LGD framework. Therefore, when the sample comprises a significant number of defaults not leading to losses, the overall LGD becomes lower, linearly impacting the risk-weighted assets (RWA) calculation. This fact must be taken into account when considering default definitions. A stricter default definition does not always (for example, 90 days past due vs. 180 days past due) reflect in a proportionally stricter RWA impact given that – even when the PD increases – the LGD can decrease significantly.

Usually, an LGD framework that aims to adhere to both business practice and regulator requirements is based on a three-step approach. The first step generally involves LGD estimation for all those contracts that have passed through the entire recovery process with the aim of deriving realized losses with proper discounting effects embedded in them. The second step incorporates into the model the early default signals, before the recovery process has started. This step entails modeling the probability of the early signs being cured (cure rate) or entering the recovery process thus generating losses (danger rate = 1 – cure rate). The final LGD is a combination of the two steps. In addition, there is the consideration that the default definitions might vary between institutions, and as a consequence different cure rates need to be estimated according to the specific framework.

5.3 Methods for LGD estimation

LGD models have to take into account both the product-specific characteristics and the underlying recovery processes. Therefore, there are various families of models that can be suitable for LGD estimation. In this section, we present a summary of some of the most common methods for predicting LGD for retail portfolios.

5.3.1 Overview of the estimation process

The objective of an LGD model is to estimate recovery rates (RR) to be applied to the whole portfolio in order to predict losses (LGD = 1 – RR). Model inputs are cash flows observed for defaulted contracts (the work-out approach) together with any relevant driver that is significant for LGD prediction. Model outputs are estimated LGD values to be assigned to the whole portfolio. Figure 5.3.1 displays the model's development steps.

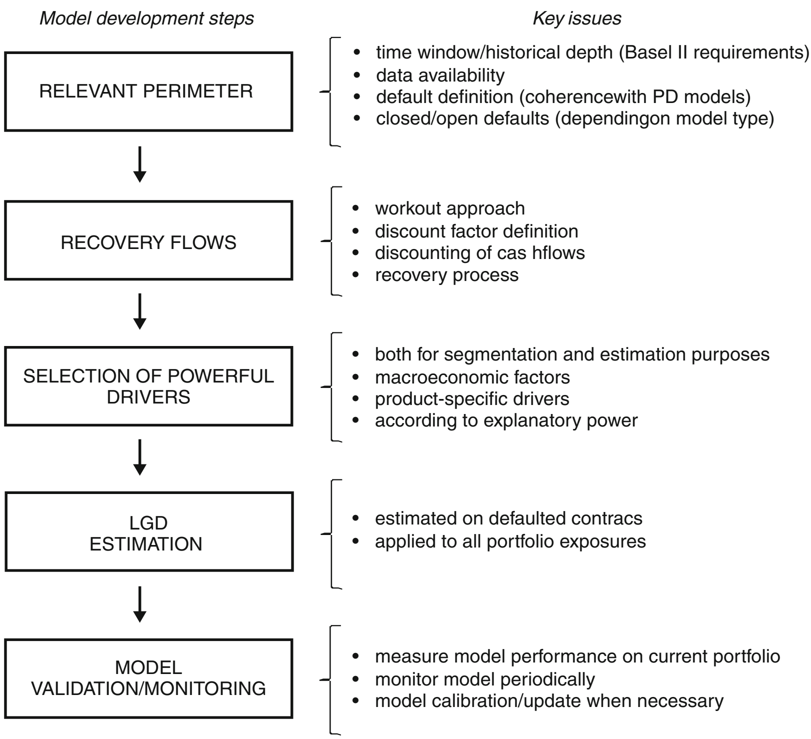

Figure 5.1 Overview of LGD estimation process

Perimeter

The construction of the development sample follows these requirements:

1. The sample should fit the default definition required by the framework as well as business collection processes.
2. All the available default history should be collected in order to verify the existence of particular trends and to choose both the development and test sample. Then, according to requirements, a Basel II model considers all available history (five years at least); however, the focus of the impairment and BAU models is more on recent history.
3. Information on both the facility and the borrower, along with any relevant macroeconomic indicator, should be added at the time of observation (time of default). These are the possible drivers that will be tested during the model development as segmentation and/or model variables.

4. On the basis of the development sample composition, then, it is important to draw early conclusions on data availability and consistency that can suggest which specific method be applied.

Recoveries

Recoveries should be attributed to each facility, and both direct and indirect costs should be taken into account and added, if appropriate, to the target variable according to the development framework. For an impairment LGD model, or a severity model to be used for business-as-usual purposes, the possibility of not using all the available history can be evaluated, as there are no specific time window requirements, unlike in Basel framework. This fact allows the definition of models much more adherent to recent trends in recoveries.

Drivers

Independent of the method used for LGD estimation, the drivers most likely to impact the LGD estimate are the following:

1. Transaction/product features: such as collateral information when available on the basis of product typology, existing guarantees and incidence of EAD (loan-to-value), remaining debt etc.
2. Borrower characteristics: geographical location (this is expected to be particularly meaningful for mortgages, because it gives information on real estate quality or the duration of court processes), existence of other debts, etc.
3. Various macroeconomic indicators

Estimation

In this subsection, we describe three comprehensive methods for LGD estimation in retail lending portfolios: conditional means, linear regression, and chain ladder. These are by no means an exhaustive list of possible LGD models; nevertheless, they cover all major modeling issues and comprise the most common and feasible methods.

For all models the target variable is the economic LGD that is computed as

$$LGD = 1 - RR = 1 - \frac{\sum_t Rec_t \delta_t - \sum_t Cost_t \delta_t}{EAD} \tag{5.2}$$

where Rec_t are recoveries observed at time t, $Cost_t$ are costs observed at time t, and δ_t is the discount factor.

Validation

As for any statistical model, LGD estimates need to be validated and their performance assessed. On one hand, a newly developed model is going to be tested on an out-of-time or out-of-sample dataset in order to evaluate the goodness of the estimates. On the other hand, the model has to go through a regular monitoring process (possibly quarterly) in order to verify it with recent data and to introduce corrections if necessary.

5.3.2 Conditional means model

Overview of statistical model – estimation process

This model is not strictly a statistical model. It is basically the calculation of an average LGD within certain segments. The first step is to derive a segmentation for the portfolio based on relevant drivers. Segmentation variables are selected on the basis of both empirical and business criteria and statistical significance with respect to observed LGD. Possible relevant drivers have been mentioned in the overview. As in the selection of drivers, segmentation can be empirically or business based or statistically based (for example through cluster analysis, decision trees etc.), or it can combine both approaches. Once the best segmentation is derived through a combination of the selected drivers, average LGDs are computed for each segment. In the application phase the current portfolio is classified according to the same segmentation, and for each contract the estimated LGD coincides with the average computed at development for the segment it belongs to.

This method is the simplest for obtaining LGD estimates. Conditional means analyses can also be considered as a preliminary step to other techniques. Being part of univariate analyses or segmentation analyses, the average LGD behaviour can suggest the appropriateness of the potential drivers to be selected, for example, a regression model, or segments for splitting the initial development sample (when sample sizes make it feasible) and proceeding to the estimation of specific models for portfolio subsets.

Example: LGD model for a personal loan portfolio

As already mentioned, conditional means models can be used as a preliminary step to regression or more sophisticated models, in order to capture relevant trends in recoveries by different drivers. The example provided in Table 5.1 illustrates possible observed LGD values for a personal loan portfolio, split by two drivers: loan purpose and distribution channel.

Table 5.1 Possible segmentation drivers for personal loans model

Driver	Value	N	Average LGD
Distribution channel	Branches	5463	83.18%
	Open market	7890	86.56%
	Total	*13353*	*85.18%*
Loan purpose	Finalized loans	6342	84.57%
	Not finalized loans	7011	85.72%
	Total	*13353*	*85.18%*

Table 5.2 Possible segmentation for personal loans LGD model

Value	N	Average LGD
Branches – Finalized loans	1259	77.45%
Branches – Not finalized loans	4204	84.90%
Open market – Finalized loans	5083	86.34%
Open market – Not finalized loans	2807	86.95%

Table 5.3 Final LGD model for personal loans

Value	N	Average LGD
Branches – Finalized loans	1259	77.45%
Branches – Not finalized loans	4204	84.90%
Open market – Finalized loans + Not finalized loans	7890	86.56%

A possible segmentation is obtained by combining the two drivers. See Table 5.2.

Table 5.3 shows an improved segmentation in which segments with similar LGD values have been joined. To obtain the best segmentation, the following should be satisfied:

1. Segment size should be large enough to guarantee robustness.
2. Segments should provide a good discrimination (high variability of average LGD between segments).
3. Segments should be uniform (low variability of average LGD within segments).

5.3.3 Regression models

Overview of statistical model

Regression models estimate LGD as a linear function of relevant selected explanatory variables (regressors). For each regressor a specific coefficient is estimated that can be considered as a weight associated with the variable in determining the LGD predicted value. The linear regression equation underlying the model is

$$LGD = \alpha + \sum_{i=1}^{k} X_i \beta_i \tag{5.3}$$

where the components are: (a) α is a constant (estimated by the model); (b) X_i are the explanatory variables (observed for each contract); (c) β_i are coefficients (estimated by the model) associated to the regressors. Model application entails assigning a specific LGD value to each contract on the basis of the observed value of each explanatory variable . The final LGD prediction is a combination of the relevant drivers weighted by the estimated parameters.

Estimation process

The method used is the so-called workout approach, whereby the recovery history of all facilities is observed and all recoveries/costs are tracked throughout the life of the default.

The target variables are the observed economic LGD, and the relevant drivers are selected through a stepwise procedure based on explanatory power and significance. Model coefficients are then estimated for the selected subset of regressors by ordinary-least-squares methods. A downturn effect can be incorporated into the model, for example by applying a conservative factor to the final LGD estimates or stressing some of the model regressors.

Example: LGD model for a mortgage portfolio

Regression models are widely used for LGD modeling purposes when dealing with mortgage portfolios, especially in a Basel II framework. According to Basel II requirements, a sample of closed charge-offs is used for fitting a regression equation. Table 5.4 shows a long list of potential regressors commonly taken into account for mortgages.

A subset of all original variables is chosen through a stepwise regression. For modeling purposes, it is convenient to group continuous variables into classes. Parameters are estimated for the selected regressors. Table 5.5 shows the final model.

Table 5.4 Long list of regressors for the LGD mortgage model

Type of variable	Variable	Description
Customer	Area	Geographic area of customer
	Income	Annual income of customer
	Age	Age of customer
	Job seniority	Year in current job
	Marital status	Marital status of customer
Contract	Vintage	Vintage of contract at time of default
	Duration	Duration of mortgages
	Installments	Number of installments of mortgages
	Delinquency	Number of arrears at time of default
	LTV	Loan-to-value ratio
	Installment/Income	Ration of installment amount to income
Macroeconomic	GDP	
	Unemployment rate	
	Saving ratio	
	House price index	

Table 5.5 Final LGD model for mortgages

Variables	Class	Estimated coefficient	P-value	Correlation with LGD
Intercept		0.07	< 0.0001	
LTV		0.35	< 0.0001	+
Vintage	0–2 years	0.05	0.0032	+
	2–3 years	0.1	< 0.0001	
	>3 years	0	< 0.0001	
Area	Area 1	0.12	0.0021	–
	Area 2 and 3	0	0.0001	+

Given such a model, if LGD is assigned to a contract with an one-year time on book, a 73 percent loan-to-value ratio, and subscribed by a customer living in Area 1[1], then the LGD is

$$LGD = 0.07 + 0.73 {}^{*} 0.35 + 0.05 + 0.12 = 49\%. \tag{5.4}$$

Downturn LGD comes from stressing, for example, LTV. A possible stress factor can be computed based on the observation of the house price trend

during a downturn period. Application of a stress factor of 25 percent to LTV leads to a model like this:

$$LGD = 0.07 + 0.73^{*}[1/(1 - 0.25)]^{*}0.35 + 0.05 + 0.12 = 58\% \qquad (5.5)$$

where the stress factor has the effect of decreasing the LTV denominator by 25 percent and therefore increasing the final LGD from 49 to 58 percent.

5.3.4 Chain-ladder model

Overview of statistical model

Chain-ladder models aim to predict future recovery curves, starting from observed ones. The starting points are vintage recovery curves computed on the defaulted portfolio. Based on predicted curves, a unique LGD average value is computed, to be applied to the whole portfolio. But whereas this method is well known in insurance as a tool for predicting losses arising from claims, it is not widely used for LGD estimation. However, given the straightforward implementation of the method, it can be extended to LGD estimates for unsecured loans. One of the pros of this method is that LGD can be estimated on the basis of all available defaulted contracts, rather than closed cases only. In fact, the chain ladder allows the forecasting of future recoveries on the basis of the latest cumulative trend independently from the current stage in the recovery process. On the other hand, estimates based on the chain ladder need to rely on a robust set of data and need to be frequently monitored, because the method is highly sensitive to outliers such as all mean value-based models (please refer also to Verdonck et al., 2007). Thus, this method can be suggested for large portfolios of unsecured loans in terms of defaults (like consumer loans or revolving credit cards whose recovery process is usually based on recursive bullet payments) rather than portfolios with a lower number of default and recoveries coming from large spot payments (for example, mortgages).

Estimation process

The starting point is the vintage recovery matrix in which recovery data are stored for each month after the default date. This matrix has the following structure: each row represents a vintage of defaulted cases and each column a single period (such as a month) of observed recovery; then each cell shows the realized absolute recoveries for the corresponding vintage (row) and observation month (column).

Table 5.6 The structure of the vintage recovery matrix

VINTAGE RECOVERY MATRIX					
default month	**EAD**	**months from default**			
		1	**2**	**...**	**n**
month 1					
month 2					
		OBSERVED RECOVERIES			
					UNOBSERVED RECOVERIES
month n					

The goal of a chain-ladder model is to estimate the unobserved portion of the matrix and then use the completed matrix to estimate LGD. Such a process is performed through the following steps:

1. Vintage recovery matrix construction (cumulative recoveries).
2. Calculation of development factors that represent the monthly recovery growth rate expected for a specific month after default, based on the available recovery history.
3. Prediction of future recoveries, filling up the lower triangle of the recovery matrix by means of the development factors (multiplicatively applied to observed recoveries).
4. Calculation of the overall recovery rate based on the completed vintage matrix.
5. Estimation of LGD as 1 – RR.

Example: LGD model for a credit card portfolio

Chain-ladder models can be successfully applied to LGD estimation for credit card portfolios, given the recovery structure. For example, collecting the recovery flows for all of the cards entering default status within a certain time window from month one to month *n*. For each observed month, the vintage recovery matrix looks like Figure 5.3.7 (n = 4).

The objective is to predict the lower triangle of the recovery matrix and use the full matrix for estimating LGD. Figure 5.3.8 shows the cumulative recoveries that are needed before calculating the development factors.

The unobserved future recoveries (i.e., the lower triangle in the matrix above) is estimated through the development factors, as shown by Figure 5.3.9.

Table 5.7 Vintage recovery matrix

OBSERVED ABSOLUTE RECOVERIES					
default month	EAD	months from default			
		1	2	3	4
month 1	1000	60	50	10	5
month 2	2300	100	40	10	
month 3	3100	100	80		
month 4	4000	150			

Table 5.8 Vintage recovery matrix with cumulative recoveries

OBSERVED CUMULATIVE RECOVERIES					
default month	EAD	months from default			
		1	2	3	4
month 1	1000	60	110	120	125
month 2	2300	100	140	150	
month 3	3100	100	180		
month 4	4000	150			

Table 5.9 Development factors calculation

OBSERVED+FORECASTED CUMULATIVE RECOVERIES - calculation					
default month	EAD	months from default			
		1	2	3	4
month 1	1000	60	110	120	125
month 2	2300	100	140	150	**=150*1.0417**
month 3	3100	100	180	**=180*1.08**	**=194*1.0417**
month 4	4000	150	**=150*1.6538**	**=248*1.08**	**=268*1.0417**
development factor			**=(110+140+180)/(60+100+100)**	**=(120+150)/(110+140)**	**=125/120**

OBSERVED+FORECASTED CUMULATIVE RECOVERIES - results					
default month	EAD	months from default			
		1	2	3	4
month 1	1000	60	110	120	125
month 2	2300	100	140	150	**156**
month 3	3100	100	180	**194**	**203**
month 4	4000	150	**248**	**268**	**279**
development factor			**1.6538**	**1.0800**	**1.0417**

Each development factor is used to derive future cumulative recoveries in a recursive way in the portion of the matrix where actual data are not available. Each forecasted cumulative recovery is therefore computed on the basis of the cumulative value in the previous column, whether it is actual data or previously forecasted data, by multiplying it by the corresponding development factor. The development factor describes the proportional incremental recovery that we expect to observe month by month after default. A reasonable expectation is for the shape of the development factor (see Figure 5.3.2) to tend to one as time after the default increases, generally with an exponential decay. The expected shape can also be used to smooth the actual development

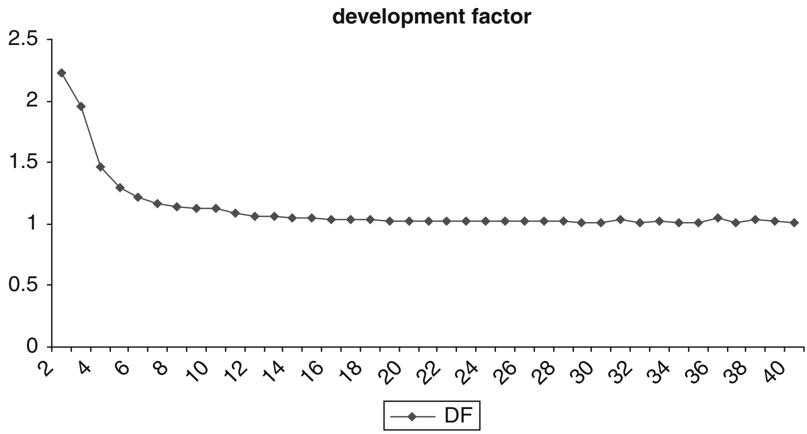

Figure 5.2 Shape of development factors' curve

factor curve whenever it appears irregular due to outliers or unexpected trends.

Once the matrix is complete, it can be used to estimate an LGD value at portfolio level as:

$$\mathrm{LGD} = 1 - (125 + 156 + 203 + 279)/(1000 + 2300 + 3100 + 4000) = 93\%. \tag{5.6}$$

This is a toy example. When extensive time windows are available, good practice dictates using only a subset of the available months to calculate development factors and/or the final LGD, in order to have values that better fit recent recovery trends. Explorative analyses should be conducted to investigate an appropriate time window. However, when applying the development factor, it is important to guarantee the factor's robustness and to avoid volatility. Reasonably, development factors can only be calculated on the basis of actual observed data up to the maximum length of the recovery cycle. However, on the basis of the expected shape of the development factor curve, extrapolation is feasible for factors of future months not yet observed and thus the matrix structure can be extended. Moreover, this method can be adapted to fit business policies; for instance, according to the expected length of the recovery process, the vintage matrix can be cut at any fixed month that allows the matrix to simulate a stock sale of default and embed expected recoveries coming from the debt sale.

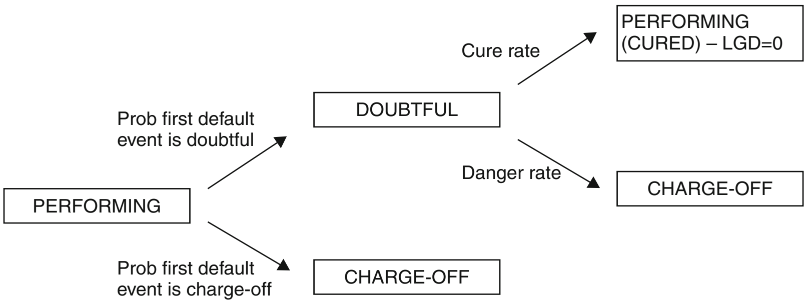

Figure 5.3 Possible default types

5.3.5 Cure-rate estimation

As already explained in the overview, cure-rate estimation is necessary when modeling different types of default. What follows is a brief description of how to introduce the cure rate into a linear regression LGD model.

The object is to incorporate into the model all the possible default statuses a contract can take throughout its life: performing, doubtful (a default status that can be cured), and charge-off (a default status that cannot be cured). See Figure 5.3.3 for a schematic of the model.

The only status generating certain losses is charge-off, whereas doubtful and performing can only lead to losses with a certain probability. In order to model such a situation, the probabilities of going from performing to doubtful and from doubtful to charge-off need to be estimated. The overall model is defined through the following steps:

1. Estimation of a linear regression for a charge-off sample (as already explained in the linear regression section).
2. Estimation of the probability P(C|D) of being cured from a doubtful status (cure rate).
3. Estimation of the probabilities P(D|P) and P(CO|P) of going respectively into a doubtful or charge-off status from a performing status.

Probabilities entering such a model need to be estimated over appropriate perimeters, and therefore specific samples need to be available for the estimation of the various steps: a closed charge-off sample for the linear regression, and doubtful and performing samples for probability estimation (with a wide enough observation period in order to monitor status changes). The model in Table 5.10 is the combination that follows:

Table 5.10 LGD model with cure rates

Account status	LGD
Charge-off	Charge-off LGD model output (regression)
Doubtful	P(C | D) * charge-off LGD
Performing	P(D | P) * doubtful LGD + P(CO | P) * charge-off LGD

1. For charge-offs, the linear regression (charge-off model).
2. For doubtful, the charge-off model weighted by the cure rate P(C|D).
3. For performing, a weighted average of the charge-off and doubtful models with weights given by the probabilities P(CO|P) and P(D|P).

Note

1. All contracts have been divided into three main areas on the basis of their house location, for simplicity named Areas 1, 2 and 3.

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6
Model Validation

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6.1 Introduction

The internal validation of rating systems is part of the general framework for rating system controls. According to both Italian and international regulatory requirements, validation activities should not be confined to empirical validation methods and tests, but should assess the overall functioning of the rating system along different dimensions that include method, the IT system and data quality, and processes and governance. Following the Basel Committee on Banking Supervision guidelines (2006, p.109), to comply with the normative framework, "banks must have a robust system in place to validate the accuracy and consistency of rating systems, processes, and the estimation of all relevant risk components. A bank must demonstrate to its supervisor that the internal validation process enables it to assess the performance of internal rating and risk estimation systems consistently and meaningfully."

This chapter focuses on the internal validation approaches of rating systems in the retail sector by taking into account the possible organizational structures for the conduction of the activities, the main tools, and processes. The chapter provides a specific focus on the quantitative aspects in terms of the analyses of models, the methodological background of the statistical tests, the interpretation of possible outcomes, and the actions to be taken according to the results.

6.2 Internal validation – organizational structures

The regulatory framework for International Basel II guidelines describes the internal validation process as a structured set of activities aimed at the

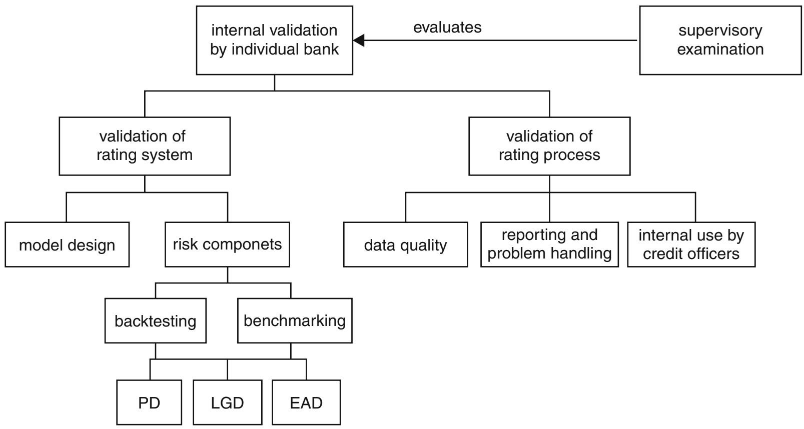

Figure 6.1 Graphical description of the key components of a validation process

examination of a rating system and an estimation process for its risk components and methods, as well as the verification of system compliance with the minimum requirements for the IRB approach. In particular, the Basel Committee on Banking Supervision (2005, p.8) provides a detailed graphical description of the key components of a validation process, reported in Figure 6.1

Local regulators acknowledge the BCBS directives through the formalization of specific guidelines, as opposed to broad characteristics of the internal validation process from the organizational, procedural and method points of view.

Specifically, concerning the first topic, local and foreign regulators have specific directives for validation activities positioned within institutions' organizational structures. These directives emphasize their prominent role in achieving an effective and efficient system for credit risk management. They address three basic structures: strategic supervision, management, and control bodies. Each structure has a specific scope and expertise. They define the bank's policies concerning rating system characteristics, roles and responsibilities to realize and assess the bank's overall quality level in terms of the accuracy and consistency of the methodological background, processes and the IT environment.

Local financial institutions acknowledge regulatory requirements by putting – in most cases – the responsibility for the definition of internal validation policies and guidelines onto the department of the Chief Risk Officer (CRO). The CRO designs and coordinates the whole validation activity flow, based on the bank's strategic directives and regulatory

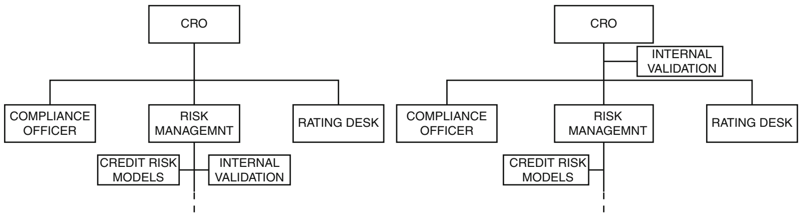

Figure 6.2 Organizational structures for internal validation

requirements such as the validation process definition, analysis dimensions, method and documentation standards, acceptability threshold values for quantitative analyses, timelines, and feasibility evaluations for action plans derived from the findings of the validation processes. In this context, the internal validation unit acts as a control body that assesses the rating system's overall functioning. From the organizational point of view, this unit can be positioned in the bank's organizational chart either directly below the CRO or subordinate to an intermediate function that oversees the entirety of the Basel II activities. This function in turn reports directly to the CRO. In the case of bank groups, strategic supervision and management activities should be performed at the corporate level that has responsibility for the validation process.

Figure 6.2 shows two examples of possible organizational structures for internal validation.

In concrete terms, several validation sub-units can be in charge of the validation activities, provided that all of the sub-units refer to the same risk management area, and that a single responsible figure is in charge of the overall process, coordination and supervision. Besides the general directions described above, Italian regulators specifically acknowledge the necessity for the functional separation of the internal validation unit in order to achieve an effective and significant system of controls. According to this requirement, the internal validation unit should be independent of the units involved in the rating assignment and credit allocation, in charge of the design and implementation of the rating system, and also of the internal review function controls the validation process and its outcomes.

6.3 The validation process

The internal validation process consists of a structured set of activities, tools and procedures aimed at assessing the accuracy and consistency of the overall rating system. According to the international regulatory

framework, in the wider context of a rating system's approval or maintenance process, this set of activities should be included in the rating system's life cycle both at an early stage of its development/application for approval and on a regular basis. This requirement usually generates two validation macro-activities – initial and ongoing – described thus. Initial validation activities take place during either the development of the new rating system, or the application to a local regulator for approval of an existing rating system, or the new release of a pre-existing rating system.

Concerning the cases of the new development and application for approval, the validation process aims to assess the positioning of the rating system with respect to the requirements set out by the regulator. Eventually, internal guidelines position the system in order to highlight criticalities, warnings, or areas of potential improvement at both the model and process levels. In the case of a new release, when significant modifications are applied to a pre-existing rating system, the validation process focuses on assessing whether the system's performance and functionality have actually improved with respect to the previous version, and – in the case of the modifications derived from validation findings – their effective responsiveness to the findings.

Consequently, the ongoing validation activity allows the bank to assess, on a regular basis, the trustworthiness of the outcomes from the periodical performance monitoring and the annual validation of the rating system. Specifically, the periodical performance monitoring aims to assess the ability of the quantitative models included in the rating system to correctly capture relevant risk components. The annual validation of the rating system, in contrast, aims at assessing whether the overall rating system is in line with the requirements set out by the regulator; and the internal guidelines highlight criticalities, warnings, or areas of potential improvement at both the model and process levels. Both in the case of initial and ongoing validation, all outcomes should be properly documented and reported to the bank's top management. In addition, all validation reports should be sent to the internal audit function.

6.4 Internal validation activities

6.4.1 Models

This subsection deals with the internal validation models of the Basel II risk components: probability of default (PD), loss given default (LGD), and exposure at default (EAD). The aim of the following subsections is

to illustrate the qualitative and the quantitative analyses that should be performed by the validation team in order to assess the goodness and the consistency of internally developed models. For each risk component the analyses are divided between model design, with the aim of qualitatively assessing the feasibility of the methodological choices as well as the overall model structure set up during the development phase, and model performance, with the purpose of investigating the suitability of the development choices and their feasibility at the time of validation from a quantitative perspective.

The validation team's role is to investigate in depth all aspects of the models, and highlight potential critical gaps with the regulatory requirements, as well as highlight gaps relating to the best practices of the market. The output of the validation assessment is a list of recommendations for each area identified as not completely satisfactory. All recommendations should state a level of priority with a reference to the critical gap detected, so that the owners can make the appropriate plans for improvement in the model.

When the availability of data permits, internal validation analyses should be performed by using a specific sample, which should be set up by adopting the same segmentation and observation selection criteria as in the development phase. The availability of such a sample allows the validation team to analyze actual model behaviour by comparing its performance with development and validation, and highlighting eventual overfitting phenomena.

Probability of default

This subsection defines the set of qualitative and quantitative analyses aimed at analyzing the methods adopted within the rating systems for the evaluations of obligors' probability of default. The PD validation model focuses on two main subjects: model design and model performance. Model design assesses the quality and appropriateness of model developmental choices, how these compare to other similar models, and whether changes exist in the population/environment that might require a revision of the choices. While model performance assesses the performance level of the model at the development stage as well as over time, model design deals with discriminatory power, calibration, and stability assessments.

Model design

One of the first topics for the validation team to evaluate concerns the availability of the model documentation. In order to investigate the

underlining characteristics of the model in depth, clear and exhaustive documentation is essential to ensure its full repeatability. The validation unit has to assess the availability and the comprehensiveness of these documents. In addition, the same level of exhaustiveness is required for third-party vendor models.

The assessment of the model design should cover the consistency of the definition of default adopted in the development and calibration of the rating model with the definition specified by the regulatory framework. A comparison between the model development's (or calibration) definition of default and the Basel II definition should be carefully performed, identifying any kind of difference between the two and any inappropriate measures aimed at correcting such a difference. Further, a check should be made as to whether or not the default definition is also in line with that applied in the credit process.

The assessment should also focus on choice of method; the assessment should evaluate whether methods (internal default experience, mapping with external data, statistical default prediction model) adopted in the development of the model are appropriate and consistent with the characteristics of the reference portfolio, its materiality, and the availability of data. Portfolios that are highly material might require much more rigor in building models. Given that there is enough data, these types of models should be developed making use of statistical techniques as well as judgmental components. In addition, comparative analyses regarding the adoption of alternative methods should be performed, and they should verify whether their outcomes support the methods currently applied; for instance, in the case of critical issues relating to quantification techniques or the scarcity of information, all necessary subjective interventions need to be undertaken in order to solve them. In any case, the subjective analyses should be consistent and not lead to an excessive discretional impact on the outcomes of the model.

In addition to the choices of method, an assessment should be made of whether appropriate and exhaustive criteria are used to select the variables. To evaluate the criteria adopted in the definition and selection of explicative variables, an assessment also needs to be undertaken for the adequacy of the process applied in the identification of the initial set of explicative factors (longlist) and in the selection of those relevant for the multivariate analysis (shortlist).

The default data used in the development of the rating model and in the determination of long-term default rates for the calibration of PD estimates should be computed at the obligor or transaction level, consistent with the development approach. Moreover, it is essential to

establish whether or not the model was developed in compliance with regulatory standards assessing whether a TTC methodology was used for calibration, and that the PD estimates are one-year estimates.

Concerning the data used by the European Parliament and the Council of the European Union Capital Requirement Directive (2006a) for the model's development, "the credit institution shall demonstrate that the data used to build the model is representative of the population of the credit institution's actual obligors or exposures". Therefore, the model must be suitable for the portfolio to which it is applied. The representativeness analysis of the development sample versus the target portfolio can be assessed through the Population Stability Index (PSI), according to the following formula:

$$PSI = \sum_i (sample\,1\%_i - sample\,2\%_i)^* \log\left(\frac{sample\,1\%_i}{sample\,1\%_i}\right) \tag{6.1}$$

where i is summed over all buckets and stands for the percentage, *sample 1%*$_i$, of the observations in the first sample used for comparison (for instance, the development sample) that is in bucket i, and stands for the percentage, *sample2%*$_i$, of the observations in the second sample used for comparison (for instance, target portfolio) that is in bucket i.

According to the best practices, a representative sample should turn in a value lower than 0.10, while a PSI between 0.10 and 0.20 indicates a low representativeness of the sample in comparison to the target portfolio. Higher values highlight the unrepresentativeness of the development sample, and the possible reasons should be investigated in depth. The representativeness should be assessed according to the relevant drivers of the target portfolio: geographic area, loan maturity, and amount issued are a few examples of the possible pertinent risk drivers.

Concerning the data for PD quantification, the adequacy of the size of the development sample and the length of the observation period should be checked in order to ensure accurate and robust estimates. Moreover, the length of the historical observation period applied in the development of the model should cover at least two years for at least one source.

Calibration should be assessed in depth, as well as the rating scale. The adequacy of criteria adopted for the identification of calibration pools should be checked to analyze whether there are relevant differentiations in terms of default rates for further segmentation drivers. In addition, all rating grades/pools should be adequately populated by measuring the number of exposures in each rating grade over the total number of rated exposures. The number of defaults observed on each rating

grade/pool should be material in order to allow a correct quantification and validation of PD estimates.

Model performance

This subsection describes the analyses that assess the performance level of the model at development (through initial validation) as well as through time (through monitoring/ongoing validation). Three modules of tests comprise discriminatory power, calibration, and stability.

The discriminatory power assessment evaluates the quality of the model in ranking obligors from good to bad. This ranking is performed using actual good/bad data. For retail models, discriminatory power tests are carried out at the model, module, and individual factor levels.

The calibration assessment validates the quality of the model by assessing how it assigns a probability of default to pools. Particularly, the objective of the analysis is to verify whether realized default rates are in line with estimated PDs, considering both automatic PDs and PDs after overriding. The analyses have to be conducted at different levels: single grades, where the consistency between PD estimates and observed default rates is verified in each rating grade; and the overall model, where the focus is the consistency between the estimated average PD and the default rate observed for the whole portfolio.

The stability assessment verifies the shifts in the population that could require a revision of the model using new data that better represents the current target portfolio. This analysis can be performed either by using the outputs of the model or through analyzing the portfolio figures.

Discriminatory power assessment

Following the main statistical test, a description of discriminatory power is useful to assess the ability of the model to discriminate between good and bad observations. Bearing in mind the focus on the retail sector, the following tests can be performed at the score, pool, and rating-class levels.

One of the most frequently used measures to assess predictive power is represented by the accuracy ratio (AR). This ratio is a synthetic index function of the cumulative accuracy profile (also known as the concentration curve, CAP). The AR creates links between the CAP of the assessed model with the CAP of the perfect model and the CAP of the random model. The AR is defined as:

$$Accuracy\ Ratio{:}AR = \frac{a_r}{a_p}$$

where a_r equals the area between the concentration curve of the estimated model and the CAP of the random model, and a_p equals the area between the concentration curve of the perfect model and the CAP of the random model. The numerator a_r is calculated as $a_r = AC - 0,5$, where AC is given by:

Concentration Area:

$$AC = \sum_{i=1}^{N} \left[B_{i-1}(P_i - P_{i-1}) + \frac{1}{2}(P_i - P_{i-1})(B_i - B_{i-1}) \right]$$

where B_i equals the cumulative percentage of bad in the *i*-th scoring class, P_i equals the cumulative percentage of the counterparties in the *i*-th scoring class, and the N equals the number of classes. The denominator a_p is given by $a_p = (1 - 0,5 \cdot B/P) - 0,5$, where B/P is the ratio between bad clients and the overall observations.

AR is a measure of the estimated model's predictive power compared to the performance of the perfect model: a value near 100 percent indicates an excellent discriminatory power that highlights the ability of the model to assign the worst scores to bad clients. A level of this measure near to zero underlines the incapacity of the model to differentiate between good and bad observations – and a negative value of the AR highlights incoherency in assigning the scores: in this case good clients have worse scores and the model is counterintuitive. Usually banks have validation guidelines that set AR thresholds and related traffic-light

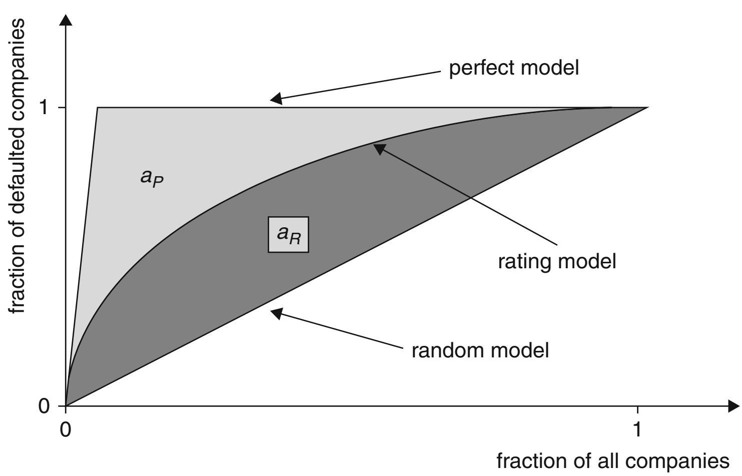

Figure 6.3 CAP curve and the areas used to compute AR

results according to different AR values. These thresholds are usually different according to predictive power assessments at different levels (overall model, segment, singe module, and individual factor).

Calibration assessment

Regarding the calibration topic, the following tests aim to assess the goodness and the conservativeness of the performed calibration with reference to the overall level as well as at the single-rating-grade level. As for the predictive power tests, the focus on the retail segment should be considered. As a result the following tests can be carried out at different levels: score, pool, and rating-class levels.

In order to assess the quality of the forecast overall, the Brier Score is an evaluation based on a comparison between the total theoretical default rate and the number of defaults observed in the validation sample. For each counterparty, the quadratic difference is calculated between the theoretical PD and the status observed:

$$Brier\ Score = \frac{1}{n}\sum_{j=1}^{n}\left(p_j - \theta_j\right)^2$$

$$\theta_j = \begin{cases} 1, & if\ j-th\ observation\ is\ defaulted \\ 0, & else \end{cases}$$

where n equals the counterparties of the sample, and pj equals the PD of the j-th counterparty. This measure assumes values between zero and one. The closer the Brier Score to zero the better the PD forecast. Banks usually define a threshold for the Brier Score in order to indicate acceptable forecasts.

The Binomial Test is used for validating PD estimates for each rating category of the internal rating systems. This test relies on the assumption of independence of the default events in the rating category under consideration. It is structured as a hypothesis test that compares the default rate of the validation sample with the maximum theoretical default rate within each grade in order to verify that the PD estimated for each grade does not underestimate the phenomenon. The test is based on verifying the following hypothesis:

$$\begin{cases} H_0: \ PD\ correctly\ estimated \\ H_1: \ class\ PD\ understimated \end{cases}$$

Given a predefined confidence level, the null hypothesis is rejected if the number of defaults p observed in the rating grade is higher or equal to a

critical value p^* that is defined as:

$$p^* = \Phi^{-1}(q)\sqrt{\frac{PD\,(1-PD)}{n}} + PD \tag{6.2}$$

where q is the confidence level of the test, PD is the theoretical PD of the class, and n is the number of counterparties of the validation sample within the class. The number of defaults observed in each rating grade is compared with the maximum theoretical number of defaults at the prefixed confidence level. The null hypothesis of a correct estimation of the PD is accepted whether the number of defaults is lower than the maximum theoretical number.

Stability assessment

In reference to the stability analysis, the purpose is to verify eventual shifts in the population that could require a revision of the model using a new development sample that better represents the current portfolio. In order to assess the stability, one of the main measures is the PSI (already anticipated by the representativeness analysis). Recalling the formula, the PSI is calculated as:

$$PSI = \sum_i (D\%_i - V\%_i)^* \log\left(\frac{D\%_i}{V\%_i}\right) \tag{6.3}$$

where i is summed over all buckets, $D\%_i$ stands for the percentage of the observations in the development sample that is in bucket i, and $V\%_i$ stands for the percentage of the observations in the validation sample that is in bucket i.

Loss given default

With regarding to the LGD model validation, this subsection defines the set of qualitative and quantitative analyses aimed at investigating the methods adopted during the development of the rating system and the performance of the LGD model. As with the PD models, validation activities foresee model design and model performance tests.

Model design

The goal of the model design analysis is to verify the adequacy and the soundness of the choice of method applied in the definition of the LGD model and to assess the adequacy and reliability of the LGD estimates. Several of the tests performed for PD models are still valid, such as the adequacy of the definition of default, the concentration of exposures, the long list of factors and the estimation process, and the availability

of a comprehensive and exhaustive documentation, as well as the size of the development sample and its representativeness with the target portfolio. As a result, the focus is on the specific characteristics of LGD models.

The validation team should assess whether all relevant information in the determination of the loss rate has been considered in the development of the model and in the choice of the final set of explicative variables. In this view, the predictive ability of risk factors not considered in the development of the model and their correlation with the explicative variables should also be considered.

The main area of the analyses of choice of method addresses the estimation of the recovery rate that must be based on the real cash flows resulting from the workout and collection process. In particular, the losses should be considered in an economic sense and must reflect the realized losses of the bank with no prevision for the future recovery rate.

Regarding the principal choice of method adopted in the development of the LGD model, the validation team should also verify that the method for LGD estimation takes into account the possibility that defaulted exposures can be cured by applying necessary adjustments to the estimates (cure rates).

The normative principle relating to estimation of the LGD deals with the definition of losses; The European Parliament and the Council of the European Union Capital Requirement Directive (2006b) propose a definition for the LGD based on a sense of economic losses with the statement, "loss means economic losses, including material discount effects, and material direct and indirect costs associated with collecting on the instrument".

Regarding the determination of the economic loss rate, the choice of method, and the criteria applied, the validation team should focus on two different aspects. The first is the loss-rate components that must be consistent with the determination of the exposure at the beginning of the default process (EAD); in case of credit transfer procedures, their treatment should be in line with the calculated LGD. Secondly, the censoring and technique used in the determination of the observed loss rate must have an economic sense without significantly modifying the distribution of the losses.

A central consideration during the validation analysis relates to the definition of the discount rate used in the determination of the economic losses. This rate, in the literature usually calculated with the method defined by CAPM (Capital Asset Pricing Model) by Sharpe (1964), has to take into account the time value of the money and also the implicit risk

in cash flow volatility resulting from the collection process (for example, through the identification of an adequate risk premium).

A critical aspect assessed in the regulator's analysis of LGD models regards the conservatism of the LGD estimates. Accordingly, the validation team should test the degree of conservatism defined by the LGD model, and the team eventually has to control whether judgmental adjustments applied in the development of the model are appropriate, especially when the model makes use of defaulted positions not closed at the development date or when the LGD model estimates a negative rate.

Regarding the conservatism of the LGD estimations, the regulatory framework imposes on banks the use of a downturn effect in the LGD values with the goal of protecting the banks from an excess of losses that cannot be estimated with only the use of historical data. The role of the validation team in this case is the investigation of the definition of the downturn effect, and the identification, carried out during the development process, of adverse dependencies between default rates and recovery rates.

Regarding the treatment of the eventual forms of protection, such as collaterals and personal guarantees obtained by the bank during the credit process, the role of the validation team is to investigate the use of these data during the determination of historical LGD values. When this information has already been taken into account in the PD calculation, the validation team should certify the absence of the information in determination of the LGD.

The last step in the validation activity for LGD models is the stress test that should be performed to verify the adequacy of the bank's capital, with the rule defined by the regulator's principles. The adequacy of the stress tests is examined on the basis of three principles regarding the soundness of stress testing, the congruity of shock hypotheses, and the stress testing frequency. The first step in the validation process of stress testing is an investigation into the internal approach used to identify hypothetical events or changes in economic conditions that could have unfavorable effects on the bank's credit exposures and on its ability to withstand such changes. During the stress testing, the bank considers several hypotheses regarding a downturn period to evaluate the adequacy of internal capital. The goal of the validation team in this case is to investigate the adequacy of these hypotheses; they should consider at least the effects of a mild economic recession. Further, regarding the frequency of the internal stress test, the regulatory framework indicates that the activity has to be performed regularly, in accordance with the nature of the risks to which the bank is exposed.

Model performance

The aim of this subsection is to introduce the main methods underlying the quantitative analyses to be performed during a validation activity for the assessment of the LGD model in order to verify the accuracy and reliability of the LGD estimates produced by the analyzed model. The analyses are divided into two categories: model discriminatory power and the comparison of estimates.

The first category refers to the analyses that aim to investigate the power of the model, in particular its discriminatory capacity, that is its ability to associate higher LGD with riskier exposure. The analyses of the comparison of estimates determine whether estimates produced by the model are in line with the historical losses that occur in the bank's portfolio. In both classes the analyses are performed at different levels: model, segment, module, and individual factors. The last part of the quantitative analyses concerns the benchmarking analysis in case the LGD model is compared with other models used in other banks or in the literature in terms of the levels of the performance of the different models.

The main step in the quantitative analyses focused on the LGD model is the computation of the receiver operating characteristic (ROC) that can be calculated to obtain a level of the model's performance in the ability to produce high estimates for positions that show high losses. Figure 6.4 illustrates the ROC curve.

The ROC values measure the performance of the LGD model in terms of its ability to assign for each chosen cut-off an LGD higher than those exposures that have a loss rate higher than the sample average (Hit Rate, HR(C)) and its inclination to assign for each chosen cut-off an LGD higher than those exposures that have a loss rate lower than the sample average (False Alarm Rate, FAR(C)). Associated with the ROC curve, the validation team should compute the AUROC values that represent the ratio between the measure of the area underlying the ROC curve and the area underlying a curve that identifies a perfect model. The AUROC presents values between zero and one, where one represents the perfect model and 0.5 the random model. The AUROC is calculated with the following formula:

$$AUROC = \sum_{i}^{n} \left[HR_{i-1}(FAR_i - FAR_{i-1}) + \frac{1}{2}(FAR_i - FAR_{i-1})(HR_i - HR_{i-1}) \right] \tag{6.4}$$

where n represents the number of cut-offs analyzed.

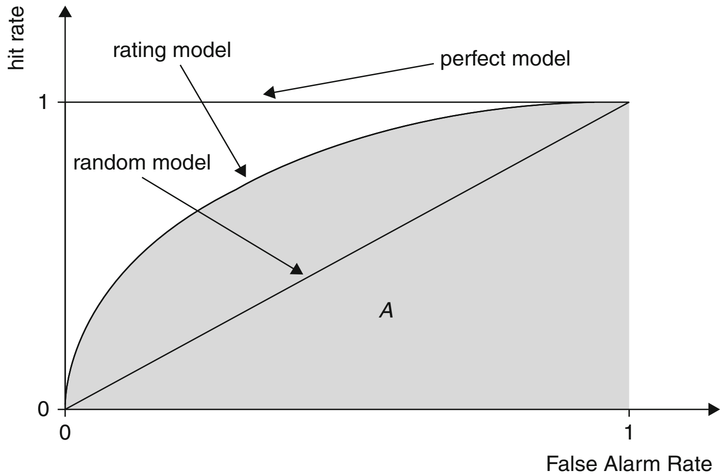

Figure 6.4 ROC curve

The analysis of the ROC curve and the value of the underlying area determine some properties of the LGD models. The area under the ROC curve can be interpreted as the average discriminatory power of the model, calculated for all possible cut-offs; the curve shows the trade-off between positions with higher LGD than the average that is properly estimated and counterparts with lower LGD that are not properly evaluated. The goal for every LGD model is to present a value of AUROC not far from that representing the perfect model; in this case the scoring model shows a high capability in properly evaluating the LGD of the counterparties.

The following analysis, Kendall's Tau, tests the model performance as a measure of association:. The concept of association measures the linear dependence that for continuous variables is expressed by the correlation. The Kendall's Tau-b can be used to compare the ranking of the estimated LGD with the observed LGD, both divided into buckets. The measure of this index reports a number between minus one and one that could be interpreted as a correlation between the observed values of LGD and the estimated values. In the case where the measures indicate one, the model shows a perfect correlation between observed and estimated; in fact the power of the model to estimate high LGD for positions with high LGD observed results is at its best. The goal for a good model is to obtain a value of this index not far from one. Kendall's Tau is defined by the

following formula:

$$\tau = \frac{2(P-Q)}{N(N-1)} \tag{6.5}$$

where P represents the number of concordant couples. A couple is defined as concordant when for i and j indexes with the observed values $LGD_i^{obs} > LGD_j^{obs}$, the model estimates values in the same order, $LGD_i^{\exp} > LGD_j^{\exp}$; at the other point, Q represents the number of discordant couples, and N the number of total couples. During the analyses the validation team should also control the estimation of the cure rate added to the model. These values can be compared with the values resulting from the analyses of the historical cure rates.

One of the most important tests to be performed during the validation activity in order to assess the goodness of the LGD estimation is a quantitative analysis of the relation between the estimates and the actual LGD. This test can also be carried out with a graphical analysis. In Figure 6.5 the values on the x-axis represent the estimated values of LGD, and the values on the y-axis represent the observed ones. Figure 6.5 shows the line that represents a one-to-one fit between the observed and estimated LGDs that is the result of a perfect model.

The quantitative test is an analysis of a linear regression of the observed values of the LGD by the estimated values. If the intercept of the regression differs significantly from zero, the model underestimates or overestimates substantially the observed values of LGD. In addition, if

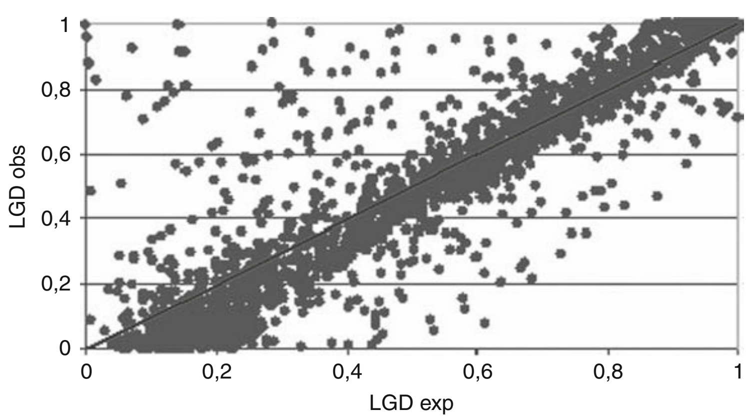

Figure 6.5 Estimated values of LGD

the coefficient of the regression for the expected values of the LGD results are statistically different from one, a powerful distortion exists in the LGD estimates.

The last part of quantitative analyses is a benchmarking analysis of the model. In this case the validation team compares the analyzed model with the LGD models that other banks use or with those in the specialized literature.

Exposure at default

This subsection describes the set of qualitative and quantitative analyses typically performed in order to validate an EAD model in accordance with the local and Basel II international regulatory framework as well as on the sector's best practice. As for the previous risk components, these analyses focus on two main subjects: model design and model performance.

Model design

As in the assessments of the previous two risk components, model design validation for EAD models focuses on the specific characteristics. All of the previous relevant topics, such as the default definition, the documentation completeness, and the sample size and its representativeness, should be evaluated as well.

First of all, compliance assessment identical to that required for the definition of the other risk parameters is performed for definition of the EAD in terms of the credit conversion factor, that is, "the ratio of the currently undrawn amount of a commitment that will be drawn and outstanding at default to the currently undrawn amount" (The European Parliament and the Council of the European Union Capital Requirement Directive, 2006b).

Focusing on choice of method, according to the regulatory framework verification should be obtained that EAD estimates are based on historically observed EAD events, and the estimates should reflect the possibility of further additional drawings after default. Furthermore, according to the sector's best practice, the validation team should verify that several possible EAD modeling approaches (cohort definition, fixed or variable time horizon) have been analyzed before choosing to adopt one. Then the team should assess the rationale and criteria driving this choice and the extent of judgmental interventions in modeling with respect to historical experience and empirical evidence. In addition to the method approach, validation analyses should also involve

the assessment of the criteria adopted in the definition and the selection of the explicative variables.

Downstream of the model's development method, validation should involve the analysis of the obtained EAD estimates to assess their representativeness of long-run experience so that they cover an entire business cycle, their conservatism, as well as the inclusion of a downturn effect.

Model performance

Model performance describes the typical set of analyses aimed at assessing, in a quantitative way, the performance level of an EAD model both at the development stage and over time. The model performance generally investigates the model's discriminatory power, its calibration, the dispersion of estimates, and the sample stability.

- Discriminatory power analyses aim to assess the ability of the model to order exposures according to their actual riskiness by calculating the measure of the area underlying the ROC curve (AUC) both on development and (where available) on the validation sample. As mentioned, admissible AUC values lie between zero and one, where one represents the perfect model and 0.5 the random model. When the validation sample is not available, model performance at development can be compared with other possible models that the bank uses or as known in the sector literature (benchmarking analysis).
- In order to assess model calibration, the EAD estimates are compared with the corresponding observed values, analyzing their mutual alignment over time as well as the conservatism of the estimates.
- The analysis of dispersion can be carried out through standard statistical measures such as standard deviation, interquartile range, range mean difference, median absolute deviation, average absolute deviation, and distance standard deviation. In a second stage, second-type dispersion measures can be analyzed, such as the coefficient of variation, the quartile coefficient of dispersion, and the relative mean difference. Further, other dispersion measures can be used, such as variance and variance-to-mean. A common way to summarize dispersion analysis is the boxplot test; this is a graphic way to represent a numeric sample through a five-number summary: minimum value, first quartile, median, third quartile, and maximum value. A parallel boxplot analysis can also be useful for assessing the stability of the validation sample with respect to the development data.
- In order to further investigate the stability between development and the validation sample, the PSI index is typically calculated. As already

recalled in the PD validation section, according to sector best practices, PSI values lying under 0.10 highlight the stability between the compared samples.

6.4.2 Process and governance

Process

This subsection illustrates a common set of methods and a minimum set of analyses and tests to assess the compliance of the IRB systems (for both entry and ongoing use) with regard to organizational features, processes, procedures, internal controls, and data flows specifically for credit risk. The validation activity can be carried out through three different types of analysis: the documentation analysis that aims to evaluate the adequacy of the documentation to regulatory requirements, the empirical analysis that aims to ensure effective implementation, and adequacy of the performances of the processes and systems; and the effective practice verification that aims to ensure the effective application of internal regulation disposals by the functions/ personnel, through interviews and on-site visits.

The validation process completes the model design controls through an in-depth documented and empirical analysis of the implemented criteria for default identification in the whole credit process from proposal to workout. Moreover, this process has to verify that the bank has set up clear criteria to identify which contract changes do not cause a default status. The default definition and credit status used for the documentation, the workout process and the reporting have to be unique. Some additional controls are required for a banking group in order to ensure a complete alignment in assigning the default status for common customers.

The verification of the bank's criteria and method for assigning exposures is intended to prevent arbitrage and/or gaming possibilities. For this reason each difference between internal and supervisory classification must be justified and documented. Specifically, to be categorized as retail exposure, the exposure of individuals is regardless of exposure size; with small and medium businesses, the total exposure needs to be less than 1 million, and loans are managed as retail exposures with part of a large pool of exposures that are managed by the bank. Empirically, the validation unit carries out controls through a coherence analysis between the output of segmentation and the input data.

The validation process also includes verifications of the goals of other control functions (different from the internal validation unit or the

internal audit) for monitoring all preliminary activities for rating assignments and for verifying on a sample basis the final ratings assigned. Usually, these kinds of controls are performed through personnel interviews supported by the collection of related documentation on the frequency, types, and internal compliance of controls, or though the verification of the presence of automatic controls in the applications involved in the process of the rating calculation and monitoring.

The requirement of replicability, integrity, uniqueness and consistency are verified through documented and empirical analysis. In particular, the analysis proves that the bank has provided each segment and each legal entity with a detailed description of variables used to segment exposures, of the rationale for its choice of internal rating criteria, and of the presence of coherence controls between the regulatory segmentation applied to exposures and the internal rating model and rating process used. These controls have to be performed for PD, LGD, and EAD assignment. Moreover, the way the judgmental evaluation can modify/integrate the automatic statistical rating has to be clearly documented by the bank. The presence of all relevant material and updated information for the rating calculation has to be assessed through controls aimed to verify the presence of a mechanism that inhibits the rating assignment. Finally, the validation unit has to verify that the bank has defined and documented roles and responsibilities for parties involved in the PD assignment process with the power to approve rating exceptions and attribute definitive ratings that specify criteria and limits. As the latter, the validation unit carries out massive verification of the consistency of the approval power to highlight anomalies in the process.

In order to assure the rating replicability, a clearly documented assignment process has to be provided, including a specification of the phases of the rating assignment: override exceptions, personnel responsible for approving override, assignment and review rating data. Verification of the uniqueness of the rating aims to control for each facility (exposure) being assigned to the same pool. Moreover, for those positions related to different departments, geographic locations or subsidiaries of the group, the bank should document policies and procedures to define unambiguously the responsibility to rate customers or to assign exposures to the pools. Further, the validation unit should investigate the frequency of rating updates in order to control that the bank has defined a regulatory obligation to review PD and LGD estimates at least on an annual basis. It should also investigate the procedures defining the corrective actions on PDs in case of indications of customer worsening coming from rating procedures or monitoring systems. From an operational point of view,

some empirical analyses should exist to check the frequency of updating the rating, to analyze the trend of expired and downgraded ratings over time, and to check the average updating frequency on expired and declined ratings.

Because Italian regulation requires an application for qualification at least three years prior to the use of the IRB approach, the bank should use ratings across the credit process from the lending phases (disbursement and renewal) to monitoring and reporting. Verification of the internal use requirement is performed to assess that the bank has calculated the PD, LGD and EAD estimates, that the internal rating estimates are effectively used during the loan's preliminary investigation, and that there is a strong relation between the results of the loan's preliminary investigations and PD estimates. Furthermore, the limits of the different approval authorities have to be defined according to the credit risk profile of the customer/transaction, represented by the pool rating of the transaction. In the required regulatory period, the bank should define the specific guidelines that will ensure the relation between the internal rating assigned and the approval of the credit lines, and follow the approval powers. The risk management function should have also analyzed the distribution of the current portfolio over the rating scale (PD scale) and have monitored its evolution. Finally, internal use validation aims to verify the use of PD and LGD internal estimates for all internal reporting to the top management and functions involved in the credit process (both business and controls functions).

For a banking group, a structured verification has to be implemented in order to ensure the coordination of all legal entities and business units within the group for the IRB system's adoption and implementation, to guarantee compliance with the regulatory requirements.

Governance

This subsection provides general guidelines on the validation activities required to test the governance of advanced risk management and measurement systems. This validation activity has to be performed both at the consolidated and at the legal entity levels, and it is carried out mainly through the documentation analysis on a yearly basis, or whenever relevant changes in internal regulation occur. The investigation areas can be divided into the duties and responsibilities of the supervisory, management and control bodies. It can also include the coordination and communication between the parent company and its subsidiaries with regard to strategic decisions on risk management.

Validation has to assess the effective engagement of the supervisory body in establishing strategic risk management guidelines and policies as well as in their periodic review. The procedures for identifying and assessing risk should be approved by the supervisory body, and this approval process has to be clearly documented. The supervisory body has the responsibility for the assignment of appropriate tasks and responsibilities for the risk-control functions in terms of consistency with strategic policies, the exercising of independent judgment, and the adequacy of resources for both qualitative and quantitative skills. Moreover, as far as the risk management and monitoring system is concerned, validation activity has to verify the safeguard of the supervisory body for its accuracy, efficiency and effectiveness in the control system in a complete and timely fashion in terms of the information system provided as well as in the functionality. The supervisory body should have an active role in adopting appropriate remediation in the case of irregularities in the risk monitoring process. With regard to the internal rating systems, the supervisory body is responsible for the approval of the adoption of the choice of system, roll-out plan and timetable, and the human, financial, and technological resources engaged. Validation has to assess the effective engagement of the management body in both its control and active duties. The management body has to assess the overall efficiency and effectiveness of the risk management and control systems, correcting shortcomings or irregularities found, and adapting the system to changes in the business environment. The tasks and the responsibilities specification has, however, to be declined by the management body in order to avoid conflicts and overlaps and to ensure that specific activities are headed by qualified personnel. Nevertheless, the management body should establish the internal reporting flows necessary to provide the governing bodies and control functions with the information needed to fully understand and manage risk factors. With regard to the internal rating systems, the management body is in charge of the implementation and establishment of the internal risk measurement systems selected; in order to perform this task, the members of the body must have an adequate understanding of the significant issues involved.

The validation also has to assess the effective engagement of the control body in monitoring that internal rating system, and checking that the risk management and control process are adequate and compliant with the regulatory requirements. The validation activity is carried out through internal policies, reports, and regulations analysis.

For the banking group, validation activity has to investigate and monitor the coordination and communication between parent company and

its subsidiaries. The strategic decisions on risk management at the group level are taken by the governing bodies of the parent company, which should adequately communicate them to the governing bodies of the subsidiaries. The validation activity is carried out through group internal policies, reports, and regulations analysis.

6.4.3 IT and data quality

This subsection provides general guidelines on the validation activities necessary to test the departmental IT system involved in the risk measurement and management processes in terms of compliance with regulatory requirements and specific company objectives.

The validation activity is carried out on a yearly basis or whenever structural IT system changes occur, and it is performed through documentation analysis, empirical verifications of data and applications, and effective practice that observes or interviews the personnel involved in the related activities.

The validation activity has to be carried out by verifying the existence of internal policies that document architectural infrastructure, existing work flows, procedures, systems, and applications used for data acquisition and data collecting. Controls based on documentation analysis aim to verify the existence and the adequacy of the standard documentation related to systems, applications, and procedures for the progress status of project activities. It also verifies the responsibility of the supervisory body for the approval of significant changes to IT architecture and applications based on it. The IT functions should be directly involved in the different phases of deployment of the internal risk measurement system. In order to verify the effective engagement of the IT functions, the validation activity has to check that the IT function is directly involved in the different phases, groups of resources are stably dedicated on homogeneous IT systems, and the knowledge of the main rating systems is kept internally (internal resources are in charge of the main IT project even if external ones are involved).

From an operational point of view, the IT system has to ensure that each dataset that provides information on the risk characteristics of the existing counterparties/operations is stored on an integrated and clearly defined platform (dedicated platform) that is completely managed by the IT function. Further, controls have to be assessed in order to verify the correct management of the IT environment's platforms and structure, with a particular focus on estimation of the risk model. Finally, the validation activity has to verify the existence of a clearly defined change-management process and related software lifecycles.

The validation of data quality assumes an important role within the validation activity, particularly for banks with internal rating systems. First of all, the control activity has to verify the existence of adequate policies or internal regulations that govern the data quality assurance processes and procedures, from the identification of the dataset to the monitoring and correction process with specific regard to the roles and responsibilities of functions or subjects in charge of the detection of the critical data and their correction. Secondly, interviews or observation of the personnel involved in the process should ensure the effective implementation of the system requirements, while direct access to data and applications should verify that all significant datasets used in the internal risk measurement system are covered by appropriate data quality processes and procedures. Finally, specific investigation has to be carried out in order to verify that controls over data quality regarding both laboratory (during model estimation process) and production environments (during model operational usage) have been set out to evaluate the completeness, the accuracy and the timeliness of input data; the coherence of data among different data sources; the information updating; the formal validity and integrity of data; and the relevance and uniqueness of data.

With specific regard to credit risk, the following additional controls are required for the IT validation unit to assess the adequacy of the integration of the rating system through the following requirements. As far as documental analysis is concerned, controls focus on the assignment of roles and responsibilities to ensure adequate data management in terms of data classification, statistical rules, and updating of data mining and data fields meaning. They also focus on the adoption of adequate track changes tools and procedures that allow the identification of the changes made and that minimize the possibility of human interventions and errors.

The most sophisticated internal IT systems are endowed with an automatic monitoring report that provides the empirical outcomes of the track changes mechanisms that track the historical data (data before changes) of the users who make the changes, who correct, cancel, and add information within the period analyzed, and mismatches. Moreover, these sophisticated internal IT systems are able to also track the results of internal account reconciliations with external data fonts of the rejected data at the different phases of the data collecting and data processing. They also track the controls (both manual and automated) performed on data and related results.

The IT system validation is completed by the verifications of the adequacy of physical security, back-up, and recovery policies. The safety

of the IT system should prevent unauthorized access as well as ensure the integrity of physical components of the system. Validation checks aim to ensure the existence of security policies for both hardware and software components; specifically, they control physical access to server rooms for authorized personnel only (with badge access, key card, etc.) and the proper logging and monitoring (access tracking mechanisms). As far as the back-up and recovery procedures are concerned, checks aim to verify consistency with business objectives and the adequacy of the frequency of record retention periods. Finally, banks have to establish and test the business continuity plan and disaster recovery procedures. The validation checks on these aspects aim to prove the existence and frequency of the recovery plans (both technical and user-end) for restoring short-term and long-term interruptions of computer processing, and the reasonability of the data file and record retention periods for the purposes of disaster recovery.

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7
Risk-Adjusted Performance Measures

Mario Anolli

7.1 Introduction

The measurement of performance is of paramount importance to credit risk management, especially in retail credit risk management where the sheer number of decisions needs to be thoroughly controlled via a standardized approach and a consistent framework. The high number of counterparties and decisions to be made calls for definite and possibly automated decision criteria and for ex post evaluation procedures concerning the rationality of the allocation of the limited capital available for the best investment alternatives on the basis of their expected (perceived) risk and return.

Risk-adjusted performance measures (RAPM) share the objective of gauging the true value added by each decision to grant credit, and is subsumed in the question of whether the capital assigned to a given transaction produces returns higher than the overall cost of the capital itself. There are two main possible uses for RAPM: to investigate the true profitability of the given business of the bank, and to serve as a measure of the Management by Objectives (MBO) framework.[1]

With reference to the first objective, a correct decision process by the top management implies that a correct measure of the expected value added by each decision is taken into account. Without factoring in the risk incurred by the bank with each decision it would be vastly incorrect to judge the profitability of the decision itself. Hence the need for a measure that encompasses both return and risk. Given the risk preference of the bank, the top management with the aid of RAPM can select which businesses to expand and which businesses to contract or eliminate because of the different levels of comparative risk-adjusted profitability.

With reference to the second objective, the decision process and its implementation should greatly benefit from some form of decentralization. In that case, each decision made at the periphery might create or destroy value for the bank, and the subjects who make these decisions have to be rewarded for their results. A correct metric for rewarding the performance of a given organizational unit has to take into account both the return generated by that unit and the risks that the same unit has incurred on behalf of the bank.

As this chapter shows, not all of the measures produce the same results for the different purposes, especially with reference to the second set of objectives. Different measures can produce different results and thus promote different (and sometimes not equally desirable) behaviors in the individuals who have to comply with the measures.

7.2 Basic risk-adjusted performance measures

The first set of RAPM can be developed on the basis of the net return and on the assets or, better, on the risk-weighted assets involved in a given credit decision (for example with the annualized return on assets – AROA – or the annualized return on risk-weighted assets – AROWA).

The AROA is defined by the following ratio:

$$AROA = \frac{Average\ Annual\ Profit\ after\ Tax}{Average\ Asset\ Value\ over\ Lifetime} \tag{7.1}$$

The average annual profit after tax in (1) is defined as the interest income plus the non-interest income, minus the cost of funding, impairment, and operational costs, that equals the profit before taxes. Subtracting the profit before taxes we get the profit after taxes of a given credit transaction. On multiannual credit operations, an average annual measure is normally used in order to smooth the effects of the possibly uneven distribution of income.

As for the denominator of (1), the average asset value over the lifetime is defined as the average value of the credit operation over its entire lifetime, which is particularly important for amortizing loans such as revolving credit cards or mortgage loans.[2]

The AROWA is defined by the following ratio:

$$AROWA = \frac{Average\ Annual\ Profit\ after\ Tax}{Average\ Annual\ Risk\text{-}Weighted\ Assets} \tag{7.2}$$

where the numerator has the same meaning as in (1) and the denominator is given by the risk-weighted assets following the Basel regulatory

Table 7.1 AROA and AROWA calculation

Interest Income	55
Non-Interest Income	32
Cost of Funding	−44
Impairment	−15
Operational Costs	−13
Profit Before Taxes – PBT	15
Taxes	8
Profit After Taxes – PAT	23
Outstanding balance	2,000
Capital at Risk – CAR	51
Risk-Weighted Assets – RWA	985
Regulatory Capital – RC	90
Cost of Equity Capital	9%
Return on RWA – RoWA	2.34%
Return on Assets – ROA	1.15%
Return on Economic Capital – RAROC	45.10%
Economic Value Added – EVA	18.41

capital definition.[3] Table 7.1 provides a simplified example of the calculation for AROA and AROWA.

7.2.1 RAPM and capital allocation

The AROA and the AROWA are stand-alone measures that do not explicitly take into account the cost of the capital being risked by the bank when it engages in a risky credit operation. A better set of RAPM (Saita, 2007) are the profitability measures jointly taking into consideration the margin of profit produced by a business and its capital at risk (CaR), where the CaR is the one-year equivalent of the ordinary value at risk (VAR) measure, and the preferable solution is when the RAPM process is inscribed into the capital allocation and capital management processes.

There are two main alternatives: portfolio models (value at risk) and bottom line models (earnings at risk).

The choice between these two approaches depends on many factors: the level at which the model is applied, the characteristics of the bank and/or of the business line, and the quality of the information set (and of the information system) available to the bank.

However, the two most used RAPM are the RAROC (risk-adjusted return on capital) and the EVA®(Economic Value Added). The RAROC – a measure based on a return over capital approach – is calculated as the ratio between the profit of a given business[4] and the CaR required by

that business:

$$RAROC = \frac{Profit}{CaR} \tag{7.3}$$

The EVA[5] – a measure based on a value generated approach – is given by the difference between profits and the cost of capital put at risk:

$$EVA = Profit - k_E CaR \tag{7.4}$$

Table 7.1. provides the values for the RAROC and the EVA as well.

Of course, the two measures provide different results: The RAROC measure is a percentage measure giving a form of return on CaR by the bank. The EVA measure provides an absolute measure of the net income generated once the cost of the risk incurred has been deducted. Of course, both measures are important, but both of them have some shortcomings:

- The RAROC can provide wrong indications because, for example, a RAROC chasing division currently with a low (high) average RAROC could (not) accept transactions producing a RAROC lower (higher) than the current cost of capital for the whole bank because its RAPM might be favorably (unfavorably) altered.
- The EVA measure can lead to the rejection of any transaction with an expected positive return but below the current cost of capital, which in principle is perfectly correct (because any given transaction either creates or destroys value). But the rejection might lead to a suboptimal decision in the short term, because the capital for which a given division does not see reasonably profitable transactions cannot be given back to shareholders. In this case, keeping the capital idle costs more for shareholders than using it at suboptimal (but positive) rates of return, especially if one considers the contribution to the general costs of the coverage of any return generating transaction.

7.3 RAROC

In order to calculate a RAROC measure, two inputs are required: a measure of profit and a measure of CaR.

As for the measure of profit, the following issues need to be addressed: the input prices, with special attention to the internal prices (the prices at which internal deals are settled); and the attribution of the costs incurred by the bank in order to operate a given business. As for the input prices, a business unit that grants credit has to fund its loans by borrowing money internally from the treasury department at a given internal transfer rate

(ITR). Because the ITRs are not (entirely) set by the market, the choice of any given ITR for any given maturity affects the profits of the credit unit: a low ITR (for example, a bid of an ITR for the relevant maturity) increases the profit of the credit unit, while the opposite happens with a high ITR (such as an ask of an ITR for the relevant maturity).[6]

As for the revenues, as already mentioned they also encompass the so-called ancillary revenues such as insurance policies and the like.

As for the general expenses attribution, the first decision is which expenses have to be considered. The best practice is to include the direct costs, that is the costs that can be avoided if the specific business or the specific operation is discontinued. Depending on the purpose of the analysis, the relevant portion of the indirect (or shared) costs also can be apportioned to a specific business unit based on an appropriate cost-sharing basis. The attribution of indirect costs might be countered on the basis of the argument that those costs are outside the scope of the action for the subjects that manage the business unit. Consequently, the attribution of indirect general costs might be useful for general management objectives (knowing the net profitability of a unit) and not useful for the evaluation of the business unit managers.[7]

7.3.1 Allocated versus utilized capital

While the definition of profit is relatively straightforward, the measure of CaR usually deserves more attention, in particular with reference to the issue of allocated versus utilized capital (Saita, 2007, p. 199; Resti and Sironi, 2007, p. 702).[8] As a matter of fact, in the capital allocation process, each business unit receives a given amount of capital that can be put at risk in order to generate revenues. The problems arise when the capital allocated to a given unit is not completely used by that unit.

Here again the criterion for the decision comes from the purpose of the RAPM measure: if its purpose is to give the top management a measure of attractiveness in terms of the risk-adjusted profitability of a certain business, the best definition relates to the utilized capital (the actual ex post risk taken). But if the purpose is to measure the performance of a given business unit, then the best measure is the allocated capital that can be considered as a production factor received by the manager of the business unit and that has to be put to good use. The problem is complicated to a certain degree by the organizational design by which the business units are allocated capital to be put at risk: if their participation in the capital allocation process is very low (top-down hierarchical approach) the business unit cannot be deemed responsible for the usage

of the capital received. This might be an indication in favor of a utilized capital measure. If, on the contrary, the business unit asks for a given amount of capital during the budget planning phase (the so-called internal market for capital), it can be deemed fully responsible for the capital available and so has to be evaluated on the basis of the capital allocated rather than on the utilized capital. The solution is far from straightforward, given the fact that in the reality of business life no clearcut solution normally prevails.

The simplest (and widely adopted) approach is the utilized capital as the only recourse, because it does not require a structured capital allocation (top-down) process. Moreover, utilized capital is frequently the definition used at the early stages in the development of a RAPM structure.

A possible solution (Saita, 2007) that tries to balance both points of view is to use both measures with different and possibly varying weights: utilized capital plus a penalty on the return based on the gap between allocated and utilized capital:

$$RAROC = \frac{Profit - p \bullet (Car_A - CaR_U)}{CaR_U} \tag{7.5}$$

or

$$EVA = Profit - (k_e - r_f) \bullet CaR_U - p \bullet (CaR_A - CaR_U) \tag{7.6}$$

where p is the penalty coefficient, and the CaR_A and CaR_U are respectively allocated and utilized capital.

The higher the penalty (*p* coefficient) the stronger the incentive for the units utilizing the capital to get the utilized capital close to the allocated capital: however careful attention should be paid by top management to the fact that different businesses are characterized by different possibilities to increase/decrease the utilized capital promptly. A broad distinction with reference to the aforementioned issue could be made between the banking book (where positions are characterized by a high level of stickiness and also of asymmetry between increasing and decreasing volumes) and the trading book (where positions, especially liquid ones, can be increased and decreased quickly and fairly easily).

A similar but more flexible solution could be to use both measures of capital at the same time and give them different weights on the basis of a set of parameters, even qualitative, as in the balanced scorecard approach.[9]

A peculiar problem with the RAROC measure is whether a single RAROC, uniform for the whole bank, has to be assigned to all the bank's business units or if different RAROCs can be used for different business units or divisions.

A single RAROC is in principle possible, given the argument that different levels of risk across different business units are properly taken into account in terms of the capital absorbed (CAR) by each business unit: riskier business units need higher CAR and thus have to produce a larger return in order to fulfill the common RAROC hurdle.

Even if as a first general approximation the uniform RAROC solution can be suggested from a strictly analytical and theoretical point of view, the uniform RAROC is not acceptable. In fact, shareholders have to be compensated for the systematic risk only (which the CAPM equation exactly postulates), while the CAR measures the whole risk instead of the systematic risk only (Saita, 2007).[10]

The problem is far from being solely theoretical. With a uniform CAR, the bank faces the problem that the units carrying larger risks can more easily exceed the RAROC threshold, but units intrinsically or behaviorally less risky can face difficulties in complying with the RAROC hurdle. Consequently, if the RAROC is used as a tool to reward the best business units, the risk of a progressive build-up of risk in the bank's balance sheet is not negligible. On the other hand, safe but relatively less profitable business lines could be progressively neglected. This process can ultimately lead to an increase in the overall cost of capital for the bank via increased risk perceived by the market. Of course, the increase in the overall cost of capital for the bank leads to a corresponding increase in the required return, thus leveling off the initial RAROC advantage.

The alternative solution to a uniform RAROC is to calculate different RAROCs for different business units. This process requires the calculation of individual betas for each business unit. The financial profession uses two opposite approaches to the calculation of divisional betas: market (or bottom-up) betas and accounting betas.

With the market approach, the beta of a given business unit is set equal to the beta of a stand-alone comparable market player. For example, for the retail credit division of a conglomerate bank, the beta of a listed credit card company can be used. There are some disadvantages with this solution. First of all there might not be a comparable competitor or, more frequently, the comparability profiles might be too narrow (in terms of size, business model and so on). A partial corrective might be to calculate a composite beta not based on a single market player but on an array of betas with different players, each one weighted by the relative

earnings produced by each business line at the bank whose composite beta has to be estimated.

The approach of accounting betas is based on the calculation of the correlation and volatility structure of a given business unit on the basis of its accounting results (mainly earnings). Accounting betas are calculated when market betas are not available due to the lack of listed firms comparable with the business line whose beta has to be calculated, but they do have some shortcomings. First of all, the frequency of accounting data (at best quarterly) can be deemed too scarce to calculate significant beta coefficients; also accounting-smoothing practices, changes in the accounting treatment of certain items, can never be completely ruled out.

When a bank adopts different RAROC targets for different business units, it has to apply different costs of capital to different amounts of capital absorbed by each business unit. Here again the problem is to discriminate between allocated and utilized capital, especially taking into account what we have been saying about the distinction between total risk and systematic (nondiversifiable) risk. One possible, even if fairly complicated, alternative (Saita, 2007), is to apply different rates to every business division (sum-of-parts method). Here again, attention should be paid to the fact that the sum of the diversified CARs can be lower than the total capital used by the bank.

Alternative solutions might be the setting of absolute profit targets calculated on the basis of different costs of capital for each independent business unit, or profits calculated based on different costs of capital and the allocated CaR, or a blend of the two.

7.3.2 Diversified versus undiversified capital

The business unit in a complex organization like a bank normally benefits from diversification economies, that is, the overall risk incurred by the bank is lower than the sum of the risks incurred by each business unit, and so the overall CaR (at bank level) is lower than the sum of individual (also called stand-alone) CaRs of the many divisions of the bank. Thus a given unit can be evaluated on the basis of its individual or undiversified CaR or on its contribution to the overall or diversified CaR.

The definition of the undiversified CaR is straightforward: it is the CaR of the business unit as a stand-alone subject.

The definition (and the calculation) of the diversified CaR (also called diversified economic capital – that is the economic capital of a business unit net of the diversification effect of the unit) is more problematical.

At best, the literature (Saita, 2007; Resti and Sironi, 2008) has developed three measures:

- The splitting method, which is quite rough, calculates the diversified CaR of each unit on the basis of the ratio of the actual CaR of a given division and the total CaR.
- The incremental CaR method postulates the calculation of the incremental CaR of any division as the difference between the overall CaR and the CaR calculated without the unit for which the incremental CaR is calculated.
- The method for the component CaR is given by the portion of the total CaR that can be attributed to the relevant component (business line) on the basis of the correlation structure of the entire portfolio.

A brief numerical example could help to make clear the differences among the three measures (Saita 2007, Resti and Sironi 2008). Let's consider a simplified bank structure composed of three divisions (business unit 1 – BU1 – a credit card business; business unit 2 – BU2 – residential mortgages, and business unit 3 – BU3 – installment loans). The economic capital (capital at risk) of the whole bank is 200, which is less than the sum of the undiversified CaRs of each business unit (250), the difference between the two being the overall diversification benefit.

The diversification benefit can be apportioned to each unit with one of the mentioned approaches.

With the splitting method, the process is very simple and the result is calculated merely by multiplying the contribution of each unit to the undiversified CaR by the ratio of the diversified overall bank CaR over the undiversified CaR.

The incremental (or marginal) CaR approach is based on the intermediate passage of calculating the marginal CaR for each business unit (given by the difference between the bank's CaR as it is, and the bank's CaR as it would be without the given business unit). Once the marginal CaR is calculated, the sum of all the marginal CaRs does not normally add up to the overall bank's CaR. Here again, in order to calculate the diversified economic capital of any unit, an adjustment is needed, and this is made by multiplying the marginal CaR of the unit by the ratio of the bank's CaR to the sum of all the BUs' marginal CaRs.

The correlation method takes into account the (actual or estimated) correlations between the different BUs; in this case, the marginal CaR is given by the difference between the bank's overall CaR and the CaR without any of the bank's BUs calculated with recourse to the correlation

Table 7.2 Diversification benefit: apportionment approaches

	BU1 – credit cards	BU2 – property mortgages	BU3 – installment loans
undiversified CaR	70	120	60
bank's overall CaR	200		
undiversified (sum of BUs) CaR	250		
bank CAR/undiversified CaR	0,8		
splitting method	56	96	48
bank CaR without BU	150	130	160
marginal CaR BU	50	70	40
diversified CaR	62,50	87,50	50,00
marginal CaR (correlations method)	36,78	76,63	38,69
diversified CaR (correlations method)	48,36	100,76	50,88
correlation coefficients			
BU1	1	0,4	0,8
BU2	0,4	1	0,6
BU3	0,8	0,6	1

matrix (Resti and Sironi 2007) and to the following formula

$$\text{Marginal Car BUi} = \mathit{Bank\ Car} - \sqrt{\sum_{k \neq i}^{n} \sum\nolimits_{j \neq i}^{n} \mathrm{CaR_k CaR_j} \rho_{\mathrm{k,j}}}. \tag{7.7}$$

When deciding whether the diversified or undiversified CaR measure is more reasonable in any particular situation, the decision has to take into account the objectives of the performance measure: If the measure is the basis for the decisions by the top management relating to the overall profitability of a given business line, diversified CaR is the most appropriate measure. If the purpose of the measure is to give performance objectives to the managers of the different business lines, the undiversified CaR has to be considered more appropriate, because the behavior of line managers has little to do with the diversification effect of the division they manage, because the diversification effect is largely beyond their ability to control.

7.4 Peculiarities of RAPM for retail credit risk management

The financial crisis has shown that risk management can be a powerful value-adding function for financial institutions: superior strategy and correct execution are not sufficient, in the absence of accurate risk management, to keep the bank profitable in the medium term. In order to properly manage retail credit risk, risk–reward models have to be provided so that the net profitability of a subject can be forecast over the expected lifetime of the lending operation. The RAPM models are normally used to manage the overall lending process: customer acceptance, loan pricing, guarantee requirements, and credit line increases or decreases.

Of course, the RAPM models have to be in place for large portfolios, and any bank has to avail itself of a thresholds framework based on the expected lending over the following year. The materiality threshold also dictates where the credit risk analysis has to be done with reference to individual borrowers or to groups of borrowers.

The grouping of borrowers is typical for retail credit risk where cost considerations discourage a detailed analysis of the individual positions, and it is normally made on the basis of segmentation drivers such as typical customer behavior, customer profitability, and socioeconomic characteristics.[11] Of course, the outcome of the segmentation process whose end result is normally the aggregation into a limited number of homogeneous portfolios composed of a large number of small-value loans, has to be correlated with the expected customer profitability, the possibility of integrating the results of the segmentation process into the lending process, and the overall accuracy of the segmentation procedure. Segmentation variables and categories are used jointly and so can give rise to a very fine granularity and a large number of clusters.

The level of model specification with reference to retail credit risk management should take into account both the level of the materiality of the portfolio and the data availability from which the model can be developed. Thus, there can be risk–reward models based on limited historical data, very basic forecasting methods (referring both to income and impairment), rough cost accounting, basic modeling, limited forecasting ability and so on. On the other hand, a bank can have a complete database of all the relevant historical data, good forecasting methods, precise cost accounting, advanced modeling, good forecasting ability and so on.

7.4.1 Model inputs

Crucial to any model that a bank might use to measure the value added by a given (set of) retail credit decision are the model inputs.

The inputs concern the following: for the single loan granted, the maturity, outstanding principal, interest, interest spread over a given index for the case of the variable rate, other revenues (that is, insurance), fees to be paid to third parties, collateral value etc.; the PD (and credit score, or rating) and the LGD as measures of risk; the prepayment probability. For the portfolio of loans the correlations (at least between homogeneous segments) and the segment prepayment rate, cost of funding, tax rate, and interest rate forecasts. As for correlations, they are normally lower for retail products than for corporate and commercial products. Conversely, the estimation of correlations for retail products is particularly difficult given, by definition, the lack of market data and the fact that banks normally employ default mode (instead of mark-to-market mode) models in order to assess the credit risk in retail portfolios, and this further increases the data granularity.

Crucial with reference to a model are some inputs that have to be thoroughly inspected in order for the opportunity to keep the assumptions to a minimum level. The main critical inputs are a behavioral input, prepayment of loans, probability of default, loss given default, and the interest rate.

Once the net rate of return is calculated, other inputs are needed to build the reference system for the calculated profitability measures. First of all we need the bank's cost of equity capital,[12] which measures the cost of the capital resources under the prudential regulation framework that the bank needs to run a given business. In other words, a decision to grant retail credit whose rate of return is higher than the cost of capital adds value to the bank, while the opposite applies when the cost of capital is larger than the net rate of return for a given credit decision.

Notes

1. Management by objectives (MBO) in management science is defined as a process that defines the objectives and measures rewards according to the attainment of the objectives previously agreed by the people involved in the process.
2. For standardization(and comparison) purposes, and in order to have less uncertainty, one can also calculate the average over the first *n* (for example, three to five) years. In that case, the reference is to the five-year (not lifetime) average.

3. Risk-weighted assets are the bank's assets, weighted according to the risk coefficients postulated by the capital adequacy regulation for a bank. According to the capital adequacy regulation, different assets show different risk weights according to the risk associated with them by following the different approaches postulated by the Basel regulation (external or internal ratings).
4. In the case of retail credit risk, the definition of revenues also encompasses the so-called ancillary revenues (ancillary with respect to the main source of revenue given by the interest rate on the loan) like insurance (payment protection insurance, property and life insurance, in the case of residential mortgages). With reference to the cost components, besides the obvious interest rate paid by the bank on the collected funds, operational costs also have to be taken into account. Normally only direct costs (variable and fixed) are apportioned to the operational costs at this stage of the analysis, and the lower the level of aggregation the less the fixed costs are included in the calculation (at the segment level only can variable costs be included in the calculation).
5. Originally (and for some time) the EVA measure (developed by Stern, Stewart & Co.) was applied to non-financial firms in the form of $EVA = NOPAT - WACC * Invested\ Capital$ where NOPAT is the net operating profit less adjusted taxes and the WACC is the ordinary weighted average cost of capital. For banks, given their peculiar liabilities structure and their regulation, only the cost of equity capital and the Capital at Risk are considered (instead of WACC and total liabilities).
6. See (Resti and Sironi, 2007) Chapter 4 for a thorough treatment of the issue.
7. We are referring here for example to the legal costs, which are generally allocated to the category of indirect costs, but that can be more than proportionally generated by certain business units (for example the exotic derivatives trading desk) rather than others (for example some forms of retail credit).
8. An additional issue is that dealing with the distinction between capital investment and capital allocation (Matten 2000)
9. The balanced scorecard approach is a management tool in which both quantitative and qualitative items are taken into account, each one with a prespecified weight, in order to get a composite score.
10. As a matter of fact, the larger the unit over which the CAR is computed, the larger the diversification benefits included in the RAROC measure, and so the closer the RAROC results to the results one would obtain on a diversified measure – and thus the smaller the error when comparing the RAROC measure to the cost of capital.
11. Specifically, data about distribution channel, loan destination (family home, holiday home, car, durable goods), client socioeconomic characteristics (age, gender, employment type, geographical area); the loan's technical characteristics (maturity, principal, guarantees and LTV); the loan's risk characteristics (scoring band, LGD band, debt to income ratio).
12. Normally the cost of capital is measured via the usual Capital Asset Pricing Model approach.

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Part III

Portfolio Credit Risk: Measurement and Management

8
Portfolio Credit Risk Modeling

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8.1 Introduction

Portfolio credit risk analysis is a relatively new field of study. In the early nineties, analysts developed a wide range of models to extend the market practice of using value at risk (VAR) as a measure of portfolios' potential losses. In this chapter, we compare different portfolio credit risk models that emphasize a common framework and we highlight how these models can be used for both regulatory and managerial purposes.

Portfolio credit risk models are at the heart of the internal capital assessment process for regulatory purposes. In order to compute the capital requirements for market risk, regulators allow banks to use internal models such as historical simulation VAR and Monte Carlo simulation VAR. However, banks are not allowed to use their own portfolio credit risk models to compute their internal capital requirement for credit risk. In the Advanced Internal Rating Based (AIRB) approach, banks exploit the Gordy (2003) model that extends the well known Merton's (1974) single asset paradigm to the whole portfolio. Therefore, in the area of credit risk, banks are allowed only to internally estimate regulatory parameters such as exposure at default (EAD), loss given default (LGD) and the probability of default (PD). These parameters, discussed in other chapters of the book, feed the above-mentioned IRB portfolio model.

The basic assumptions underlying the IRB portfolio model are not always in line with managerial issues in banking. Thus, the incentive to develop portfolio credit risk models for managerial purposes is different from that relating to models for regulatory purposes. In practice, portfolio credit risk models are used for a wide range of purposes, such as portfolio management, risk-based pricing, capital allocation and stress testing.

This rest of this chapter is organized as follows. The next section describes the fundamental idea underlying portfolio credit risk models and their use in practice. The following section reconciles the IRB regulatory formula with the best known portfolio credit risk model. Next is a case study that illustrates how to use portfolio credit risk modeling in credit risk management.

8.2 Portfolio credit risk modeling

The market analysis of portfolio theory transforms trading activities from a philosophy of picking winners to one where investors aim to hold an efficient portfolio (Elton et al., 2010). The central feature of this theory is an efficient portfolio that maximizes the expected return for a given level of risk, simultaneously minimizing the risk for a given level of return. Recognition of this correlation is the key to the benefits of holding a well diversified portfolio. However, while this approach has driven equity portfolio management over the last decade, it is still not widely applied to credit assets. Credit portfolios are not as liquid as equities; thus, despite the growing interest in credit instruments, this market cannot be compared to the equity market. In addition, from a statistical point of view, portfolios of credit assets are not normally distributed, and the distribution of losses is asymmetric. Another, more fundamental, problem is the estimation of expected return, risk and correlation. For credit assets, these parameters are determined by: the PD, the volatility of the PD, LGD, and the correlation of defaults. However, there is limited data on the historical performance of credit assets from which to estimate these parameters. For the very same reason, and different from market risk analysis (Jorion, 2006), even back-testing these models is troublesome. In the case of stand-alone measures of the risk and return of individual credits, there is an increasing array of choices. However, when we consider the whole portfolio we need additional instruments. In order to deal with these problems, the public release of portfolio credit risk models began in the mid-1990s. Almost contemporaneously, CreditMetrics™, CreditRisk+™ CreditPortfolioView™ were created.

According to Gordy (2000) and Koyluoglu and Hickman (1998), a portfolio credit risk framework requires the consideration of some crucial risk parameters. The most important parameters are: EAD, LGD, PD and measures that summarize the dependency structure of defaults. In portfolio credit risk studies, the analysis of the loss distribution is mainly focused on the PD mechanics. Default probabilities vary as a result of changing

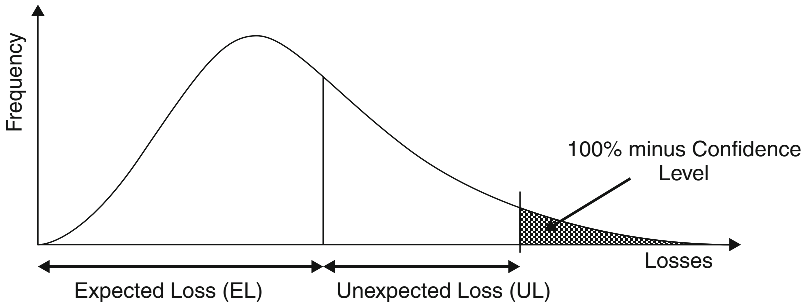

Figure 8.1 Loss distribution: expected and unexpected loss

economic conditions, so at any given point in time debtor default probability is dependent on the state of the world. At the same time, changes in credit drivers that affect conditional default probabilities determine default dependency structures among debtors. Therefore, in portfolio models the evolution of the relevant systemic and sector-specific credit drivers play a crucial role in determining the loss distribution.

Figure 8.1 shows that the goal of portfolio models is to derive the portfolio loss distribution. This is usually asymmetrical, the probability (frequency) of small losses being higher than the probability (frequency) of high losses. Starting from the loss distribution, the unexpected loss (UL) can be computed; it is the difference between the capital at risk, CaR, (at a given confidence level) and the expected loss (EL). Given a confidence level $(1-\alpha)$, the CAR can be defined as the smallest portfolio loss (l) such that the probability that the loss will exceed l is no larger than α:

$$CAR_{1-\alpha} = \inf_{l} \left(L > l\right) \leq \alpha. \tag{8.1}$$

However, if the CAR is considered a measure of downside risk it suffers from two severe deficiencies: it is not sub-additive, and it is insensitive to the size of loss beyond the pre-specified threshold level. For these reasons, in addition to CAR, the expected shortfall, ES, is useful to consider because it corresponds to the expected loss exceeding the CAR:

$$ES_{1-\alpha} = E\left[L \middle| L > CAR_{1-\alpha}\right] = \frac{1}{\alpha} \int_{q>1-\alpha}^{1} CAR(q)dq. \tag{8.2}$$

Figure 8.1 shows the ES as the black area underlying the loss distribution exceeding the CAR threshold. According to Equation 2, each loss that exceeds the CAR threshold is weighted by the corresponding probability (frequency) reported on the vertical axis.

The ES is, however, sub-additive and provides information about the amount of loss exceeding the CAR. Thus, portfolios with a low ES should also have a low CAR. In addition, under general conditions, the ES is a convex function and a coherent measure of risk as well (Acerbi and Tasche, 2002).

8.2.1 Regulatory capital, risk-weighted assets, and economic capital

Regulatory capital plays an essential role in banking activity. In fact, banks are required to respect a capital ratio between regulatory capital and risk-weighted assets (RWA). The total capital ratio (at the individual level) must be no lower than 8%:

$$\begin{aligned}\text{Regulatory capital } \geq & 8\%\ [(\text{RWA Credit Risk}) + (\text{RWA Market Risk}) \\ & + (\text{RWA Operational Risk})]\end{aligned}$$

The regulatory capital is computed by first of all considering the following two elements: paid-up share capital (common stock) and disclosed reserves. Within certain thresholds, other financial instruments can be added, such as undisclosed reserves, asset revaluation reserves, general provisions/general loan-loss reserves, hybrid (debt/equity) capital instruments and subordinated debt.

In order to compute the credit risk from RWA, the Basel II capital accord (BCBS, 2006) allows banks to exploit alternative approaches: standard, IRB foundation, and IRB advanced. For both foundation and advanced, a portfolio credit risk model is used to compute the UL of the credit risk. The UL is in turn used to compute the RWA. The portfolio credit risk model underlying the IRB formula can be compared to other portfolio credit risk models.

Concentrating on managerial approaches, the definition of economic capital is usually the UL. In particular, according to BIS (2009), we can state that the economic capital that can be defined as the methods or practices that allow financial institutions to consistently assess risk and to attribute capital to cover the economic effects of risk-taking activities, has increasingly become an accepted input into decision making at various levels within banking organizations. Economic capital measures may be one of several key factors used to inform decision making in areas

such as profitability, pricing, and portfolio optimization – particularly at the business-line level. Such measures are also used, primarily at the consolidated entity level, to assess overall capital adequacy. The increased use of economic capital by banks has been driven by rapid advances in risk quantification methodologies, greater complexity and sophistication of banks' portfolios, and supervisory expectations that banks must develop internal processes to assess capital adequacy beyond regulatory capital adequacy guidelines that are not designed to fully reflect all the underlying material risks in a given bank's business activities.

Economic capital is the amount of capital needed to support ULs at a certain confidence level (over a predefined holding period). Managers usually relate this confidence level to an (implied) default probability of a target rating agency. The underlying idea is that economic capital is the amount of capital to be allocated to support the credit risk business unit in relation to the target default probability implied by the target rating. Thus, for instance, for a target S&P rating of AAA, the implied default probability corresponds roughly to 0.03% and the corresponding appropriate confidence level is 99.97% (100% – 0.03%). For regulatory purposes, the confidence level is set at 99.9%.

8.3 Default models

In order to obtain the loss distribution function described in Figure 8.1, we assume as given the EAD and LGD. In addition, not only do we need to consider the probability that an individual debtor may default, but also we need to know the joint PD for debtors belonging to the same portfolio. Aiming to obtain the joint PD, we need to consider the following three elements: the unconditional probability of default, the creditworthiness index, and a framework that links the default probability to the creditworthiness index.

First of all we need to define the so-called unconditional PD. Indicating with τ the time of default of an obligor i that operates in the sector j, we denote $PD_{i,j}$ the unconditional PD by time $t$as follows:

$$PD_{i,j} = P\left(\tau_{i,j} \leq t\right) \tag{8.3}$$

where we usually consider the one-year holding period. In the portfolio credit risk models, the one-year holding period assumption has a correlation with the conventional period needed to modify credit portfolio composition in order to offset risky positions (for example via securitization programs or loan credit policy) as credit loan portfolios are

usually non-traded in capital markets, different from securities and bond portfolios.

The second component of the model to obtain the joint PD is an index that represents the creditworthiness of each debtor. This index is a variable that represents the financial health of the debtor. The financial literature usually considers the $Z_{i,j}$ to be distributed as standard normal random variable (that is, with zero mean and unit variance). The creditworthiness index is assumed to be related to the economic scenario through a linear multifactor model as follows:

$$Z_{i,j} = \sum_{p=1}^{P} \beta_{j,p}\zeta_p + \sigma_{i,j}\varepsilon_{i,j}, \tag{8.4}$$

where the variable ζ_p represents the economic environment and, in order to ensure that the variable $Z_{i,j}$ has a unit variance, the following assumption is:

$$\sigma_{i,j} = \sqrt{1 - \sum_{p=1}^{P} \beta_{j,p}^2}. \tag{8.5}$$

All obligors $\varepsilon_{i,j}$ are independent (from ζ_p) and identically distributed standard normal variables. For each debtor, $\varepsilon_{i,j}$ represents the idiosyncratic random component.

Equation (8.4) shows that debtors belonging to the same sector j share the same sensitivity factors with respect to ζ_p. Thus, all obligors in a sector have a common standard deviation, denoted by σ_j. We can further investigate Equation 4 by highlighting that the variable ζ_p can be represented through the set X_k of macroeconomic and the set X_s of the sector-specific variables. Thus we can rewrite Equation (8.4) as follows:

$$Z_{i,j} = \sum_{k=1}^{K} \beta_{j,k}X_k + \sum_{s=1}^{S} \beta_{j,s}X_s + \sigma_j\varepsilon_{i,j}, \tag{8.6}$$

where

$$\sigma_j = \sqrt{1 - \left(\sum_{k=1}^{K} \beta_{j,k}^2 + \sum_{s=1}^{S} \beta_{j,s}^2\right)}. \tag{8.7}$$

Furthermore, we can express $Z_{i,j}$ as function of the sector creditworthiness index Y_j. This index is common to all debtors belonging to sector j

as follows:

$$Z_{i,j} = \theta_j Y_j + \sigma_j \varepsilon_{i,j}, \tag{8.8}$$

where θ_j is the sensitivity with respect to Y_j.

Equation 8 becomes crucial for all portfolio credit risk modeling. In particular we can distinguish between the factor model (FM) approach and the sector model (SM) approach. In the first case, for sector j, the creditworthiness index depends on a set of macroeconomic and the sector-specific variables. The SM approach, however, only considers the sector variables. The portfolio credit risk framework developed by Prometeia considers both the above described approaches but emphasizes that the SM index can be represented as a linear function of the macroeconomic variables.

The third element to obtain the joint PD is the framework that links the default probability to the creditworthiness index. The conditional PD is the probability that a debtor defaults conditional on a scenario:

$$PD_{i,j}(X) = P\left(\tau_{i,j} \leq t|X\right), \tag{8.9}$$

where, according to the model on which we rely, a scenario X that comprises macroeconomic variables X_k and the set of sector-specific variables X_s.

Given the definition of economic sectors and scenarios, some models assume that all debtors in a given sector share the same conditional default probabilities. Thus, the above representation collapses into the sector j default probability. This assumption is particularly useful in portfolios where risk concentration has little relevance. However, this hypothesis does not usually hold in practice. For this reason as we will highlight in describing the Prometeia approach, both name and sector concentration risks need to be considered.

8.3.1 Regulatory formula

The goal of the regulatory IRB approach is to compute the credit portfolio UL described in Figure 8.1 and to define the minimum regulatory capital for financial institutions in a one-fits-all approach. In order to achieve this goal, the IRB capital requirement formula relies on the so-called asymptotic single risk factor (ASRF) model. The total value of the firm's assets is equal to the value of the stock plus the value of the debt. Loan default occurs if the market value of the firm's assets falls below the amount due to cover debts (Merton, 1974). Thus, the default distribution of a firm is a Bernoulli distribution derived from the distribution of

the value of the firm's asset returns. In this situation, the debtor's creditworthiness index can be considered (under a certain hypothesis) to be the standardized return of the debtor's assets. In the case where debtors belonging to the same sector are statistically identical, they share the same default boundary. Default of an obligor occurs when the creditworthiness index falls below a given boundary. Generally, we start by assuming that the creditworthiness index corresponds to the normalized asset return $R_{i,j}$. In the IRB framework, a single common factor φ and an idiosyncratic noise component $\varepsilon_{i,j}$ drive this index:

$$R_{i,j} = \sqrt{\rho_{i,j}}\varphi + \sqrt{1-\rho_{i,j}}\varepsilon_{i,j}, \tag{8.10}$$

where $\sqrt{\rho_{i,j}}$ is the correlation between the asset return $R_{i,j}$ and the common factor φ (Duffie and Singleton, 2003). Both φ and $\varepsilon_{i,j}$ are independent and identically distributed standard normal random variables. Therefore, $R_{i,j}$ has a standardized normal distribution. The component φ represents the risk common to all debtors in the portfolio. The component also shares the same economic meaning of Y described in the previous section, but it is unique and common to all sectors. On the other hand, $\varepsilon_{i,j}$ is the risk specific to debtor i. Equation 10 indicates that the assets of all firms are multivariate and normally distributed. And the equation indicates that the assets of two debtors i and m are correlated with the linear correlation coefficient $E[R_i, R_m] = \sqrt{\rho_i}\sqrt{\rho_m}$. Typically, asset return correlations and default correlations are not the same, because the default correlations are smaller than the asset correlations (Finger, 1999).

We define a binary random variable $D_{i,j}$ for each debtor. This random variable takes the value of one (meaning that the debtor i, belonging to sector j, defaults) with probability $PD_{i,j}$ and the value of zero with probability $(1-PD_{i,j})$. According to Merton's (1974) approach, we have:

$$\begin{aligned} D_{i,j} &= 1 \quad \text{if } R_{i,j} \leq \Phi^{-1}(PD_{i,j}), \\ D_{i,j} &= 0 \quad \text{if } R_{i,j} > \Phi^{-1}(PD_{i,j}), \end{aligned} \qquad \text{(11) and (12)}$$

where Φ is the cumulative distribution function of the standard normal distribution. Thus, emphasizing that $PD_{i,j}$ is the unconditional default probability, the default probability conditioned to a specific scenario

φ_{scen} can be derived as follows:

$$\begin{aligned} P\left[D_{i,j}=1|\varphi_{scen}\right] &= P\left[R_{i,j}\leq \Phi^{-1}(PD_{i,j})|\varphi_{scen}\right] \\ &= P\left[\sqrt{\rho_{i,j}}\varphi+\sqrt{1-\rho_{i,j}}\varepsilon_{i,j}\leq \Phi^{-1}(PD_{i,j})|\varphi_{scen}\right] \\ &= P\left[\varepsilon_{i,j}<\frac{\Phi^{-1}(PD_{i,j})-\sqrt{\rho_{i,j}}\varphi}{\sqrt{1-\rho_{i,j}}}|\varphi_{scen}\right] \\ &= \Phi\left[\frac{\Phi^{-1}(PD_{i,j})-\sqrt{\rho_{i,j}}\ \varphi_{scen}}{\sqrt{1-\rho_{i,j}}}\right] \end{aligned} \tag{8.13}$$

Under certain conditions, Vasicek (1977) shows that Merton's single asset model can be extended to a model of the whole portfolio. The portfolio model used in the advanced IRB approach (Gordy, 2003) is derived from Vasicek's model.

In order to compute the credit capital requirement, once the portfolio credit risk model is identified the banks must supply as inputs the credit risk parameters: EAD, LGD, PD, correlation and the effective remaining maturity (M). Given these inputs, the IRB capital requirement is computed by calculating capital charges on a loan-by-loan basis, and then aggregating these up to a portfolio-wide capital charge.

In order to describe the IRB approach in more detail, we assume that we have a portfolio with N debtors (we omit the subscript j to ease the notation) with different exposures EAD_i, asset correlations ρ_i, probabilities of default PD_i, and losses given default LGD_i. The portfolio loss (L) can be computed as $L=\sum_{i=1}^{N} EAD_i LGD_i D_i$. Assuming as given EAD_i and LGD_i, the randomness is only on D_i. In the case where $N\to\infty$, we can derive the $(1-\alpha)$ percentile of the loss distribution by substituting the value of the indicator function D_i through the $(1-\alpha)$ percentile of the conditional default probability described in Equation 13 as follows:

$$L_{1-\alpha}=\sum_{i=1}^{N} EAD_i\ LGD_i\Phi\left[\frac{\Phi^{-1}(PD_i)-\sqrt{\rho_i}\Phi^{-1}(1-\alpha)}{\sqrt{1-\rho_i}}\right]. \tag{8.14}$$

According to Figure 8.1, this percentile corresponds to the CAR at level $(1-\alpha)$.

We further investigate the loss distribution concentrating on the so-called unexpected loss. Given the $(1-\alpha)$ percentile of the loss distribution, the unexpected loss is computed as the difference between

the $VAR_{1-\alpha}$ and the expected loss $E(L)$, as indicated below:

$$L_{1-\alpha} - E(L) = \sum_{i=1}^{N} EAD_i \; LGD_i \left[\Phi\left(\frac{\Phi^{-1}(PD_i) - \sqrt{\rho_i}\Phi^{-1}(1-\alpha)}{\sqrt{1-\rho_i}} \right) - PD_i \right]. \tag{8.15}$$

This is the general formula that, considering maturity adjustments, the Basel II IRB approach uses to compute the credit capital requirement. For this purpose, the $(1-\alpha)$ level is set at 99.9%. The correlation parameter, as well as the maturity adjustment, depend on a set of variables specifically described in the Basel II accord (BCBS, 2006).

Therefore, grouping debtors into sectors, in the case where the number of debtors belonging to each sector converges to infinity $N_j \to \infty$, we can rewrite the IRB formula as follows:

$$L_{1-\alpha} - E(L) = \sum_{j=1}^{J} EAD_j LGD_j \left[\Phi\left(\frac{\Phi^{-1}(PD_j) - \sqrt{\rho_j}\Phi^{-1}(1-\alpha)}{\sqrt{1-\rho_j}} \right) - PD_j \right]. \tag{8.16}$$

Equation 16 is a closed-form formula that allows for the computation of the unexpected loss for the entire portfolio as the sum of individual losses.

8.3.2 Economic capital measurement

A crucial element of portfolio credit risk models is the estimate of the default dependency structure. Dependency modeling is an important link between the Basel II risk-weight function (with supervisory imposed correlations) and internal portfolio credit risk models.

In this section, we consider different ways to compute the portfolio economic capital (unexpected loss). We emphasize the critical assumptions that characterize alternative approaches and stress the importance of risk parameter estimates. We can obtain different loss distributions (and consequently different unexpected losses) according to the model on which we rely.

In what follows we concentrate on the following approaches: multifactor probit, multifactor logit, and Prometeia. In Table 8.1, we highlight the core elements of these models. According to Koyluoglu et al. (1999), our goal is to provide evidence that there is a coherent framework underlying alternative approaches.

Table 8.1 Portfolio credit risk model's key elements

	IRB formula	Multifactor Probit	Multifactor Logit	Prometeia
Reference model	Merton (1974)	Merton (1974)	Econometric	Econometric
Probability distribution of the creditworthiness index	Normal	Multivariate normal	Multivariate normal	Multivariate normal
Creditworthiness index factors to be fitted*	1	K + S	S or S*J	P*J
Conditional PD probability distribution	Normal	Normal	Logit	Logit
Crucial assumptions, simulation mechanics	$N \to \infty$, closed-form formula	Monte Carlo simulation of the credit-worthiness index	Monte Carlo simulation of the credit-worthiness index	Monte Carlo simulation of the credit-worthiness index, aggregation of debtors in clusters
Individual contribution	Bottom-up	Top-down	Top-down	Top-down

*Note: K, S, J, and P represent the number of variables as described in previous subsections.

Starting from the IRB formula (one-factor model) as described in previous subsections, we can describe the idea underlying the so-called multifactor probit model. The key difference between this approach and the IRB formula (see Equations 15 and 16) is the fact that in the multifactor environment the evolution of the economy is described through K+S factors instead of only one. We do not have a closed-form formula to compute the percentile of this multivariate distribution. Thus, we need to simulate these K+S factors through Monte Carlo simulations.

As emphasized in Equation 16, where we grouped debtors into sectors, the multifactor probit approach assumes that each sector has a large number of debtors $N_j \to \infty$. The default of debtor *i* in sector *j* occurs when $Z_{i,j}$ (according to Equation 4, $Z_{i,j}$ represents the creditworthiness index of obligor *i*belonging to sector *j*) falls below a given boundary, γ_j. Because of the previously described assumptions, this threshold is the same for

all debtors in sector j. Thus,

$$PD_{i,j} = P\left(Z_{i,j} < \gamma_j\right) = \Phi(\gamma_j). \tag{8.17}$$

We can state that the conditional default probability for sector j, considering Equation 6 and scenarios $X_{k,scen}, X_{s,scen}$, is as follows:

$$\begin{aligned}
PD_{i,j}(X_{k,scen}, X_{s,scen}) &= P\left(Z_{i,j} < \gamma_j | X_{k,scen}, X_{s,scen}\right) \\
&= P\left(Z_{i,j} < \Phi^{-1}(PD_j) | X_{k,scen}, X_{s,scen}\right) \\
&= P\left(\sum_{k=1}^{K} \beta_{j,k} X_k + \sum_{s=1}^{S} \beta_{j,s} X_s + \sigma_j \varepsilon_{i,j} < \Phi^{-1}(PD_j) | X_{k,scen}, X_{s,scen}\right) \\
&= P\left(\varepsilon_{i,j} < \frac{\Phi^{-1}(PD_j) - \left(\sum_{k=1}^{K} \beta_{j,k} X_k + \sum_{s=1}^{S} \beta_{j,s} X_s\right)}{\sigma_j} | X_{k,scen}, X_{s,scen}\right) \\
&= \Phi\left(\frac{\Phi^{-1}(PD_j) - \left(\sum_{k=1}^{K} \beta_{j,k} X_{k,scen} + \sum_{s=1}^{S} \beta_{j,s} X_{s,scen}\right)}{\sigma_j}\right),
\end{aligned} \tag{8.18}$$

where both macroeconomic X_k and sector-specific X_s variables are considered in order to identify the default threshold.

Aiming to derive the loss distribution, CAR, ES and the UL, we cannot simply rely on exogenous parameters; we need to generate the random vectors X_k and X_s. In other words, we generate vectors X_k and X_s through Monte Carlo generations, and for each simulation we compute the portfolio loss. After generating thousands of scenarios, we obtain thousands of portfolio losses that can be ordered to obtain a loss distribution similar to that represented in Figure 8.1.

In order to compute these losses, when $N_j \to \infty$, we can rely on the law of large numbers highlighting that the conditional loss distribution converges to the mean loss over that scenario, and the conditional variance becomes negligible. Hence, the conditional portfolio loss corresponds to the sum of the expected losses of each obligor that are aggregated at a

sector level, as follows:

$$L(X_k, X_s) = \sum_{j=1}^{J} EAD_j LGD_j PD_j(X_k, X_s). \tag{8.19}$$

Once the portfolio loss for each scenario is computed, then the loss distribution for calculating the CAR, ES, and UL can be obtained.

This framework can be extended to different settings other than the normal ones. In particular, we can consider the logit model proposed by Wilson (1997). Here, the PD of a debtor belonging to sector *j* is related to the sector creditworthiness index Y_j as follows:

$$PD_j(Y_j) = \frac{1}{1 + a_j \exp\left(b_j Y_j\right)}. \tag{8.20}$$

Thus, it is crucial to figure out the creditworthiness index to be considered and its functional relation with both macroeconomic and sector-specific variables.

The Prometeia portfolio credit risk model sets out from an econometric perspective. The key element of the Prometeia model is to consider both the systemic and the concentration risks, and the method underlying this model is to shock macroeconomic factors and to catch their impacts on default probabilities. For more details about the Prometeia approach, see the next chapter.

Accordingly, the Prometeia approach catches both the impact of macroeconomic shocks as well as the name and sector portfolio concentration. After obtaining the overall banking risk, according to Gordy (2000), we can exploit the following well known equation:

$$VAR(L) = E_{PD} \lfloor VAR_L (L|PD) \rfloor + VAR_{PD} \lfloor E_L (L|PD) \rfloor . \tag{8.21}$$

We separate the risk due to the name concentration (the first element on the of the right side of the equation) from the systemic risk (the second element on the right side of the equation). Through these mechanics, we compute the contribution of each debtor (and eventually its sub-portfolios) to the overall banking risk, which can be represented through CAR, ES, UL and other measures derived from the portfolio loss distribution.

8.4 Case study: portfolio analysis

In Table 8.2 we describe a credit portfolio consisting of 10,000 debtors belonging to the following classes: corporate, small business, private and other.

Table 8.2 shows the most important variables of the analysis. We focus on performing counterparties by stressing that the average PD and average LGD are not weighted on EAD (the expected loss of Table 8.2 cannot be computed directly by inferring from these average portfolio values).

According to the portfolios described above, we calculate the loss distribution by using analytical credit risk information at the debtor level (EAD, LGD, and PD) as well as details concerning the economic sector

Table 8.2 Comparison the portfolio's key elements

	Corporate	Small business	Private	Other
EAD	78,996	298,376	557,659	64,969
Debtors number	50	890	9,022	38
Average portfolio PD	1.67%	4.30%	3.93%	0.34%
Average portfolio LGD	32%	24%	33%	62%
Expected loss E(L)	657	3,823	6,113	77
	0.83%	1.28%	1.10%	0.12%

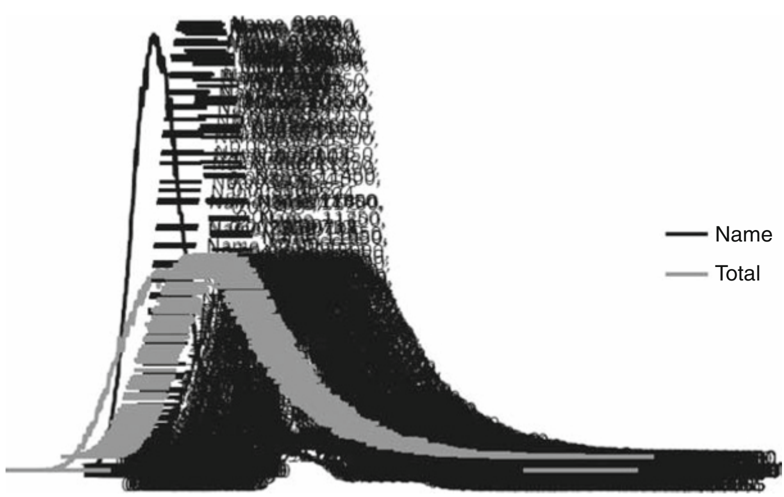

Figure 8.2 Portfolio total and name loss distribution

where they operate. In Figure 8.2, we show the total loss distribution and the loss distribution due to the name concentration.

The distributions in Figure 8.2 come from considering the correlation estimated on a set of macroeconomic variables such as GDP and the unemployment rate. In the case where we recalibrate these estimates in order to obtain the same correlation of the (Basel) IRB approach, we obtain higher ULs, as described in Table 8.3. In particular, the UL of the above portfolio, at the 99.9% confidence level, is 21,627 and corresponds to 2.16% of the total EAD in the case where we consider the original FM, while it becomes 46,184 (4.62% of the EAD) when we apply the recalibrated factor model.

We can compare these risk measures with the IRB measures. In order to apply the standardized approach, we need information on the RWA that is a function of the nature of each debtor and operation. On the other hand, aiming to estimate the IRB capital requirement, we need the internally estimated credit risk parameters – EAD, LGD, and PD – that were also required to derive the internally estimated loss distribution. In order to compute the capital requirement, we exploit the 8% coefficient applied to the RWA. In the standard approach, the weight used to compute the RWA is assumed to be on average less than 100% (in our case it is roughly 81%).

Because of their underlying assumptions, the capital requirement IRB model is applied at the elementary level and aggregated for the entire portfolio (closed-form formula). In this case, debtors' risk contributions correspond to their capital requirements. In portfolio credit risk

Table 8.3 UL estimated by the factor model

	Original factor Model	Recalibrated factor model
Unexpected loss U(L)	21,627	46,184
Unexpected loss/EAD	2.16%	4.62%

Table 8.4 Portfolio risk measures (original factor model)

	Original factor model	%/EAD
Unexpected loss U(L)	21,627	2.16%
Capital requirement (standard)	59,131	5.91%
Capital requirement (IRB advanced)	39,596	3.96%

Table 8.5 Unexpected loss: sub-portfolio vs. marginal contribution

	UL Sub-portfolio	Contribution	Concentration		Regulatory	
			Name	Sector	GA	Sector add-on
Corporate	10,847	5,742	4,274	1,468	6,930	359
Small business	8,773	7,105	1,408	5,697	933	523
Private	9,573	8,655	1,319	7,337	434	435
Other	10,051	125	125	0	10,125	45
Total	39,244	21,627	7,125	14,502	18,422	1,362

models where the loss distribution is obtained (through Monte Carlo simulations) by considering the portfolio as a whole, this correspondence does not exist, whereas in this latter case, the issue of computing the obligor contribution to the overall credit risk arises. As emphasized in the previous section, according to the variance decomposition, Table 8.5 shows the incremental contribution of each debtor to the portfolio loss according to the debtor's variance contribution to the portfolio's overall variance. In addition, we emphasize the role played by name and sector concentrations; evidently, name concentration is particularly high for the corporate sub-portfolio while sector concentration plays a key role in sub-portfolios with a high number of debtors (private and small business). In particular Banca d'Italia considers the granularity adjustment (GA) requirement in order to highlight the name concentration. The "Associazione Bancaria Italiana" (ABI), which is an association made up by Italian banks, proposes a methodology to measure the sector concentration add-on; both these values have to be added to the regulatory capital to obtain an overall measure of the capital requirement. In Table 8.5 we compare the Prometeia name and sector UL components to the GA and sector add-on regulatory requirements.

We emphasize that where we compute the sum of losses (ULs) by considering customer sector groups, we obtain results different from those obtained on the portfolio as a whole. In order to control for this drawback, we emphasize in a specific column the contribution to the overall risk of each debtor and, consequently, customer sector. This latter sum corresponds to the unexpected loss computed on the portfolio as described in Table 8.3. It is useful to note that the sector capital requirement add-on has a different magnitude compared to the UL sector contribution. This is due to the fact that it is simply an "add-on" to be added to the regulatory capital.

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9

Stress Testing, Capital Planning, and Risk Integration

Tiziano Bellini and Lorenzo Bocchi

9.1 Introduction

The term "stress test" describes a range of techniques used to assess the vulnerability of a portfolio to major changes in the economic environment or to exceptional but plausible events. In order to use the IRB approach for computing the credit capital requirement, Basel II requires banks to carry out a stress test analysis. Basel II also requires stress testing for Pillar II purposes within the ICAAP. In addition, stress testing clearly becomes very useful from a managerial point of view because it helps identify risk sources and define strategies to handle negative events. Stress testing induces banks to focus on their key risk exposures and induces them to improve model calibration in order to take into account the types of worst cases as described, among others, by the Committee of European Banking Supervisor (2010) and the European Banking Authority (2011).

Credit portfolio models are widely used in areas such as portfolio management, risk-based pricing, customer and product analysis, management incentives and capital allocation. In order to emphasize the role played by these models in risk management practice, in the next section we describe the fundamental idea underlying stress testing by showing how to implement a stress test. Then we investigate the role of portfolio credit risk models in the capital planning process emphasizing the key role of risk-adjusted performance measures as a paradigm for effective capital allocation. The last section is devoted to risk integration.

9.2 Stress testing

As emphasized in Basel II discipline, a stress test process should be able to capture the link between dramatic changes in the economic environment and the bank's portfolio. A bank must have in place sound stress test processes for use in the assessment of capital adequacy (BCBS, 2006). Unfortunately, Basel II has not yet established specific guidelines on how to carry out a stress test; however, the European Banking Authority (EBA, 2011), following the Committee of European Banking Supervisor (CEBS), gives details on how to carry out the stress-testing procedure for major European banks. Figure 9.1 illustrates the stress-testing procedure.

The first required step in stress testing is to identify the scope of the test, the perimeter of the analysis, and the risks to be stressed. Thus, once specified that our goal is the credit risk analysis, the next step is to define the scenarios that will be tested. The CEBS (2010) recommends some important activities; in particular, Guideline 6 says that institutions should perform sensitivity analyses for specific portfolios or risks, and Guideline 7 says that institutions should undertake a scenario analysis as part of their stress-testing suite. This analysis should be dynamic and forward-looking, and incorporate the simultaneous occurrence of events across the institution. Banks need to consider historical as well as hypothetical scenarios to carry out their stress test. When designing scenarios, banks should consider the impact of a recession (at least two quarters of negative GDP increase).

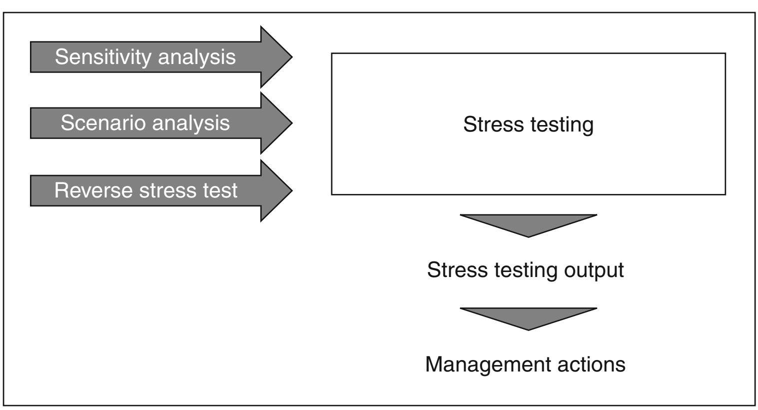

Figure 9.1 Stress-testing framework

9.2.1 Stress testing in practice

In what follows we essentially concentrate on the stress testing of default probabilities, but we can extend our framework to the other credit risk parameters as indicated by EBA (2011). We distinguish between sensitivity and scenario analyses. In a sensitivity analysis, we need to apply an exogenous shock to default parameters: in our case a probability of default (PD) shock. In a scenario analysis, we need to investigate the relation between economic factors and the risk parameter that we are studying, in our case the PD. In order to estimate the parameter vector for the stress test, the analysis of creditworthiness indexes is useful (Bellini and Riani, 2011).

In our stress-testing framework we rely on the Italian economic environment by considering the time series of a transformation of the quarterly Bank of Italy default rates $Y_{j,t}$ computed at sector level $j = 1,\dots,J$, and time $t = 1,\dots,T$. According to Equation 6 of the previous chapter, these default rates represent the creditworthiness index of sector j for each time t. In order to highlight the link between these rates and the overall economic setting, we execute a regression analysis where the independent variables are the macroeconomic variables $X_{p,t}$, where $p = 1,\dots,P$ and $t = 1,\dots,T$. In other words, we carry out the following multivariate regression:

$$Y_{j,t} = \sum_{p=1}^{P} \eta_{j,p} X_{p,t} + \varepsilon_{j,t}. \tag{9.1}$$

Once the P-dimensional parameter vector η_j for each sector j is obtained, we are able to carry out the stress test analysis described by the CEBS (2010) guidelines.

From a practical point of view, when we estimate default probabilities (Altman and Haldeman, 1995), we consider a set of microeconomic elements $\Gamma_{i,j}$ such as balance sheet ratios and indices of the firm's health. Thus, assuming that debtor-specific default probabilities vary according to their corresponding creditworthiness index, using the logit approach (Wilson, 1997) we estimate default probabilities as follows:

$$PD_{i,j} = \frac{1}{1 + \exp\left(-\Gamma_{i,j} - Y_j\right)}. \tag{9.2}$$

Assuming that $PD_{i,j}$ varies according to Y_j, we can represent shocked default probabilities as follows:

$$PD_{i,j}^{shocked} = \frac{1}{1 + \exp\left(-\Gamma_{i,j} - \Delta Y_j\right)}, \tag{9.3}$$

where ΔY_j is a function of the shocked macroeconomic factors:

$$\Delta Y_j = \sum_{p=1}^{P} \eta_{j,p} \Delta X_p. \tag{9.4}$$

Macroeconomic shocks on each p-variable ΔX_p are obtained by applying the stress scenario to each macroeconomic factor X_p (we highlight that the logit model can be extended to the probit or to other models). Thus, aiming to obtain the shocked default probabilities we first of all identify the macroeconomic scenario to be considered. Thus we compute its variation with respect to the ongoing one by using the above equations. According to the CEBS (2010) guidelines, we can consider historical or hypothetical scenarios.

9.2.2 Stress testing and Prometeia economic capital model

The stress-testing mechanics described above are at the heart of the Prometeia economic capital model. In fact, in the previous chapter, we emphasized that in the logit model (Equation 20), the PD of a debtor belonging to sector j is related to the sector creditworthiness index Y_j as follows:

$$PD_j(Y_j) = \frac{1}{1 + a_j \exp\left(b_j Y_j\right)}. \tag{9.5}$$

Moving from this representation, the key feature of the Prometeia credit portfolio model is to consider both the systemic and the concentration risks as described in Figure 9.2.

The key elements of this model can be summarized as follows:

- Aggregation of debtors into clusters (c) according to their potential loss (Credit Suisse Financial Products, 1997) and the computation of

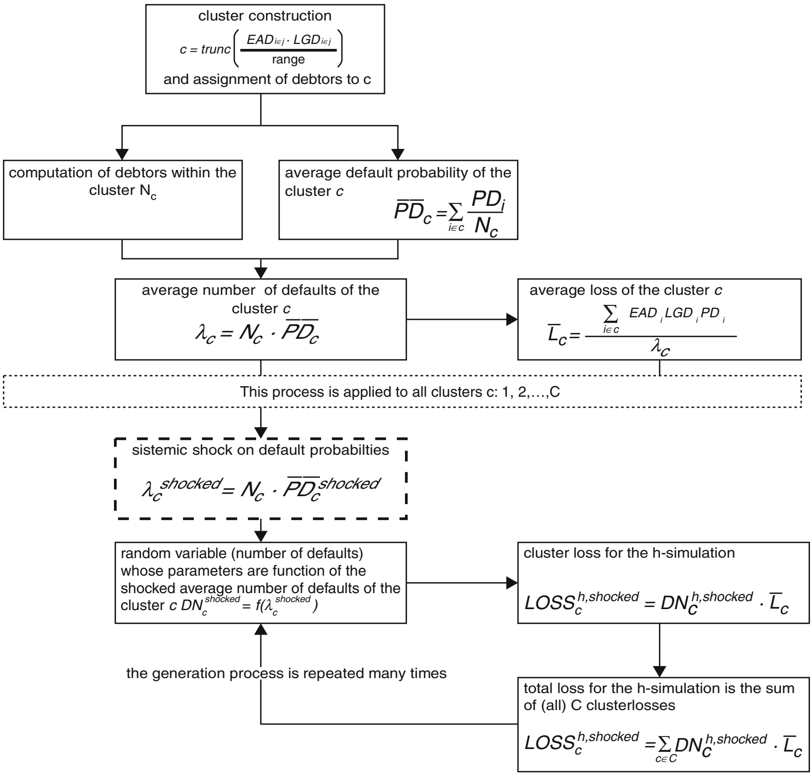

Figure 9.2 Prometeia credit portfolio mechanics

credit risk measures (number of debtors, average *PD*, average default number, average loss) at the cluster level.

- Introduction of the systemic shock through a factor-based model (probit or logit) that relies on the econometric analysis of an index that represents the health of the sector *j* for that cluster.
- Generation of the variable default number of the cluster (Credit Suisse Financial Products, 1997) through a Monte Carlo simulation approach based on Poisson or Binomial random variables (Glasserman and Li, 2005). Having shocked the variable that represents the average cluster's number of defaults ($\lambda_c^{shocked}$), we randomly generate a Poisson or Binomial variable with parameter $\lambda_c^{shocked}$. In this way, for the *h* iteration, we first obtain the cluster loss as a product of the number of cluster *c* defaults times the average loss for cluster *c*. Thus, the

overall portfolio loss is obtained by aggregating the loss of all clusters. We repeat this procedure many times and thus obtain the portfolio loss distribution.

In other words, as described in Figure 9.2, the Prometeia approach relies on the analysis of the link between macroeconomic factors and the PD. Thus, once this relation (logit or probit) is identified, a Monte Carlo process is carried out to generate macroeconomic scenarios that affect default probabilities. For each simulated ΔX_p, we derive ΔY_j and therefore $PD_{i,j}^{shocked}$. The shocked *PD* is used as the parameter of the random variable default number $\lambda^{shocked}$. This random variable (default number) is generated – for each iteration h – to obtain the number of defaults in the cluster c (as described in Figure 9.2). For each scenario, a portfolio loss is computed. The loss distribution is the collection of those losses.

9.2.3 Case study: stress testing

We continue our analysis by concentrating on the portfolio described in Table 8.2 of the previous chapter. The first task we need to face in stressing PD is to identify the stress we wish to apply. To identify a scenario, we can consider a hypothetical or an historical setting. The EBA (2011) identifies an hypothetical scenario that considers the macroeconomic European environment after the crisis of 2007. A number of stringent assumptions have been adopted that aim at ensuring the overall consistency of the stress to be carried out by a group of major European banks; these scenarios are described more in detail in the Annexes of the EBA's notes on methods.

In order to identify the scenario to be used, instead of exploiting the above-mentioned EBA (or another hypothetical) scenario, we can concentrate on an historical scenario. We can, for example, consider the default rates' time series for the Italian economic system as described in Figure 9.3.

Moving from EBA 2011 wide test scenarios, in Table 9.1 we show both the impact of the macroeconomic factor shock on the PD and the effect of the LGD changes on the overall portfolio risk measures. In particular, we modify the portfolio by replacing the original LGD (of the tranche secured by real estate) with the IRB foundation with a 45 percent value. We consider the following stress test: stress 1 in which only the LGD is changed, stress 2 in which the macroeconomic factors are shocked (impact on PD), and stress 3 in which both the LGD and PD are shocked.

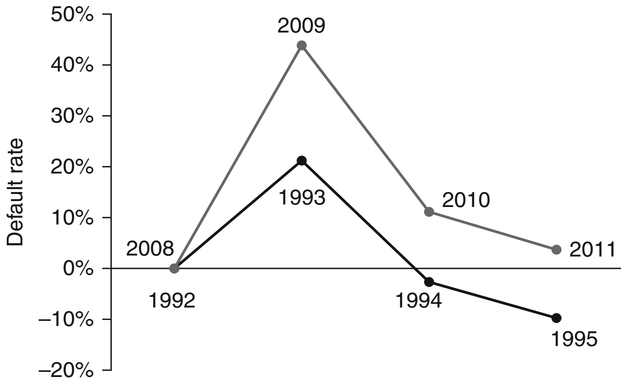

Figure 9.3 Evolution of default rates for the whole banking system: Comparison of alternative stress test scenarios

Table 9.1 clearly shows that the increase in stress-testing magnitude amplifies the impact on the IRB capital requirement and the unexpected loss (UL).

9.3 Managerial portfolio analysis: from loan policies to capital planning

Banks use economic capital both at a business-unit level and at the firm-wide level. At the business-unit level, the most important use of economic capital covers the following areas:

- **Credit portfolio management**. According to the results presented in studies such as Rutter Associates LLC (2004), the use of credit portfolio management for reducing economic capital seems to be less dominant than for "management of concentrations" and for "protection against risk deterioration".
- **Risk-based pricing**. Risk-based pricing typically incorporates the variables of a value-based management approach. For example, the pricing of credit risk products comprises the internal transfer rate on funds, the expected loss, the allocated economic capital, and extra returns as required by shareholders. Economic capital influences the credit process through the computation of an interest rate considered to be adequate for increasing (or, at least, not decreasing) shareholders' value.

Table 9.1 The stress test's impact on capital requirements and UL

	Corporate	Small Business	Private	Others	Total
EAD	78,996	298,376	557,659	64,969	1,000,000
Debtors number	50	890	9,022	38	10,000
Average PD (*)	1.67%	4.30%	3.93%	0.34%	3.84%
Average PD^{stress2} (*)	3.95%	6.83%	7.48%	0.45%	8.91%
Average LGD^{stress1} (*)	32.33%	24.44%	33.23%	62.10%	38.02%
E(L)^{original} (**)	0.83%	1.28%	1.10%	0.12%	1.07%
E(L)^{stress1} (**)	0.83%	1.70%	1.58%	0.12%	1.46%
E(L)^{stress2} (**)	1.99%	2.10%	2.07%	0.14%	1.95%
E(L)^{stress3} (**)	1.99%	2.68%	3.07%	0.14%	2.68%
IRB requirement^{original} (**)	7.13%	4.78%	3.46%	0.58%	3.96%
IRB requirement^{stress1} (**)	7.13%	6.75%	5.43%	0.58%	5.64%
IRB requirement^{stress2} (**)	10.14%	5.82%	4.85%	1.11%	5.32%
IRB requirement^{stress3} (**)	10.14%	8.04%	8.02%	1.11%	7.74%
U(L)^{original} (**)	7.27%	2.38%	1.55%	0.19%	2.16%
U(L)^{stress1} (**)	7.82%	3.21%	2.21%	0.19%	2.66%
U(L)^{stress2} (**)	7.87%	3.67%	2.29%	0.23%	2.77%
U(L)^{stress3} (**)	8.39%	3.74%	3.27%	0.28%	3.52%
Standard requirement(**)	5.18%	7.72%	5.40%	2.91%	5.91%

(*) Weighted on EAD.
(**) % on EAD.

- **Customer and product profitability**. The measurement of performance can be extended to the customer and product level through the analysis of customer and product profitability (Bellini, 2012). Such an analysis aims at providing a broad and comprehensive view of all the revenues, operational costs and risk costs (both in terms of provisions for expected losses and of shareholders required returns on, consequently, economic capital absorption) generated by each individual customer or product.
- **Management incentives.** These become deeply ingrained in internal decision-making processes. Thus, the use of economic capital needs to be extended in a way that directly affects the objective functions of decision makers at the business-unit level. This extension is achieved by influencing the incentive structure for business-unit management.

At the firm-wide level, the most important use of economic capital covers the following areas:

- **Relative performance measurement and loan policies**. In order to assess relative performance on a risk-adjusted basis, banks calculate risk-adjusted performance measures where economic capital measures play a key role. The most commonly used risk-adjusted performance measures are the risk-adjusted return on capital (RAROC) and shareholder value added (SVA) for different business units in the credit portfolio (such as corporate, SME, retail and so on). These measures can be used to identify the most effective loan policies for the bank to be carried out in order to maximize the overall risk-adjusted performance measures.
- **Capital planning**. Many banks allocate their economic capital to each business unit in their budgeting process. This process is also part of strategic planning and target setting (for example, profit, capital ratio, or external rating). In order to facilitate business growth that improves risk-adjusted profitability while operating within an overall risk appetite set by the board of directors, many banks establish internal reporting and monitoring frameworks based on economic capital. At the same time, it is useful to communicate to stakeholders the key features of bank planning. The major external communication channels include disclosure of firm-wide reports for investors, dialogue with supervisory authorities, and the dialogue with rating agencies.

9.3.1 Case study: loan policies and capital planning

As we anticipated, economic capital plays a key role in budgeting and capital planning. But traditional measures such as ROE (return on equity) do not allow for the comparison of business units with different risk profiles. In order to compensate for this drawback, risk-adjusted performance measures (RAPM) are usually exploited. The most known RAPM is the RAROC (risk-adjusted return on capital), computed as follows:

$$RAROC = \frac{NET\ INCOME}{EC} \cong \frac{IM + SR - OC - EL}{EC}, \tag{9.6}$$

where IM stands for intermediation margin, SR for service revenues, OC for operating costs, EL for expected loss, and EC for economic capital.

RAROC is useful for carrying out both ex post and ex ante performance analyses. To evaluate the historical return of different business units, we compare the historical RAROC, while for budget and planning purposes we rely on target values.

Table 9.2 RAROC analysis with EAD as-is vs. EAD target

	Corporate	Small Business	Private	Other	Total
EAD As-is	78,996	298,376	557,659	64,969	1,000,000
EAD Target	67,146	387,887	585,547	51,975	1,092,555
UL As-is	5,742	7,105	8,655	125	21,627
UL Target	3,152	6,394	8,222	88	17,856
IM+SR-OC As-is	1,629	10,686	17,266	239	29,820
IM+SR-OC Target	1,924	13,890	18,132	250	34,196
EL As-is	657	3,823	6,113	77	10,670
EL Target	589	4,750	5,896	56	11,291
(IM+SR-OC-EL)/EAD As-is	1.23%	2.30%	2.00%	0.25%	1.92%
(IM+SR-OC-EL)/EAD Target	1.99%	2.36%	2.09%	0.37%	2.10%
UL/EAD As-is	7.27%	2.38%	1.55%	0.19%	2.16%
UL/EAD Target	4.69%	1.65%	1.40%	0.17%	1.32%

Aiming to identify the most effective mix of loans, we can analyze a credit portfolio computing the RAPM at different levels. In particular, we can carry out a graphical analysis, concentrate on the study of portfolio concentration, and distinguish among customers belonging to alternative businesses. Thus, once this research is completed by a given date ("as-is" analysis), we can figure out the overall market perspectives and identify our strategic banking goals. In order to do so, exploiting scatter plots can be useful for the comparison of credit sub-portfolios. Aiming to achieve this goal, in Table 9.2 we summarize the key figures of our analysis comparing the as-is to the target portfolio that is studied at the business-wide level.

We concentrate first of all on the distribution of the volumes (expressed in terms of EAD) among business units. Our bank is a commercial one whose customers are mainly private and small businesses. After identifying the distribution of the credits, their economic performances become interesting. These performances are computed comparing revenues, costs and risks. We show that corporate business is the worst performer because of its size and risk–return relation, while small business is the best performer. Because of this as-is and risk-return structure, the target analysis focuses on the reduction of the risk (unexpected loss) for the entire portfolio and in particular on corporate business.

At this stage, moving from the as-is analysis, we pursue the goal of increasing revenues for the entire bank. Thus, we allocate the EAD to the best performing business after moving it from the worst performing ones. This reallocation is carried out with consideration to the maturity of each operation; in other words, if there are loans with maturities of ten years, we consider them as fixed and we cannot renegotiate their conditions. This exercise helps us to understand whether we have to exploit credit derivatives or other techniques to mitigate the risks of the ongoing portfolio. In Table 9.2 we highlight the potential improvement of our portfolio due to the optimization of loan policies.

In Figure 9.4, we represent on the horizontal axis the ratio EL/EAD, while on the vertical axis we have the ratio $\frac{IM+SR-OC-EL}{EAD}$. The dimension of bowls represents the EAD. Through the above strategy, each business is moved from the right side to the left (risk reduction) and from the lower to the upper area (revenue increase).

As we anticipated, there is a close connection between loan policies and capital strategy. In particular, in conjunction with the portfolio analysis we pursue the goal of optimizing the capital allocation. Thus, we

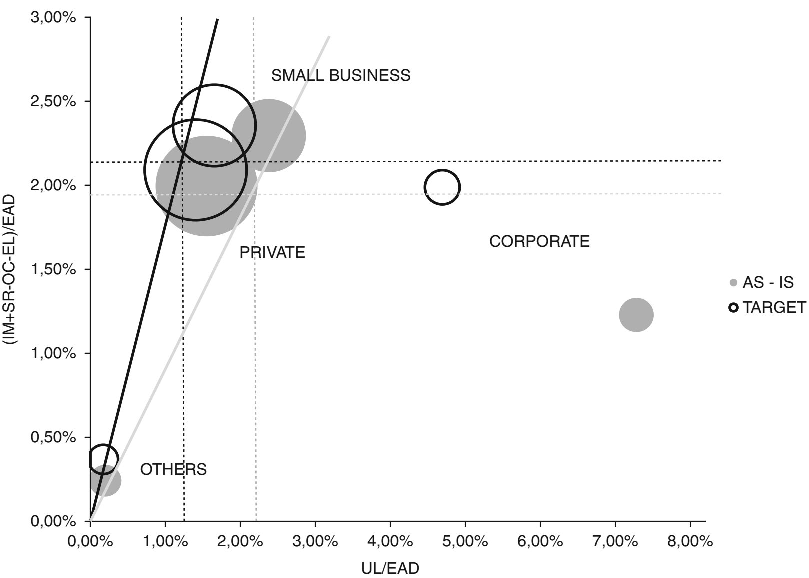

Figure 9.4 Credit strategies: RAROC approach

move along the optimal capital frontier that maximizes the risk-return performance and allocates the capital effectively.

Thus far, we have concentrated our analysis on credit risk issues only. However, when we examine the bank as a whole, other risks must be taken into account. In particular, economic capital does not depend only on credit risk. In the next section we devote our attention to risk integration.

9.4 Risk integration

According to Kretzschmar et al. (2010), banks' economic capital can be defined as the amount of resources that a financial institution requires in order to operate as a solvent concern at a specified confidence level over a given time horizon. Usually, economic capital is set to equal a percentile of the bank's loss distribution (value at risk, VAR) or the expected value of losses exceeding a given threshold of the same distribution (expected shortfall, ES). In both cases, we need to identify the loss distribution. In the modular approach, each loss distribution is computed individually and the economic capital is obtained as a sum of the independent risks. However, this approach might not be adequate in the face of the impact of crises, which emphasizes the complex interactions among risk factors and financial instruments. Evidently, to aggregate different risks, dependencies have to be considered. In order to elicit these relations, top-down and bottom-up approaches have to be developed.

In the top-down approach the idea is to start from the marginal distribution of individual risks and aggregate them through a joint distribution function.

Some authors exploit elliptical distributions, but others rely on copulas (Bellini, 2010). In both cases, some crucial assumptions are used to merge different kinds of risks into an overall economic capital measure (Rosenberg and Schuermann, 2006). An alternative perspective to tackle these issues is to model at a micro-level the interactions between macroeconomic variables, risk factors and individual financial instruments. Changes in macroeconomic variables can have an impact on the value of financial instruments by affecting risk factors (such as an increase in risk-free interest rates due to macroeconomic changes causing a reduction of fixed-rate credits) or they can influence the value of financial instruments directly (such as a reduction in the gross domestic product usually being associated with an increase in default probabilities).

In Figure 9.5, we summarize these approaches by emphasizing the fact that in top-down approaches we individually compute market, credit,

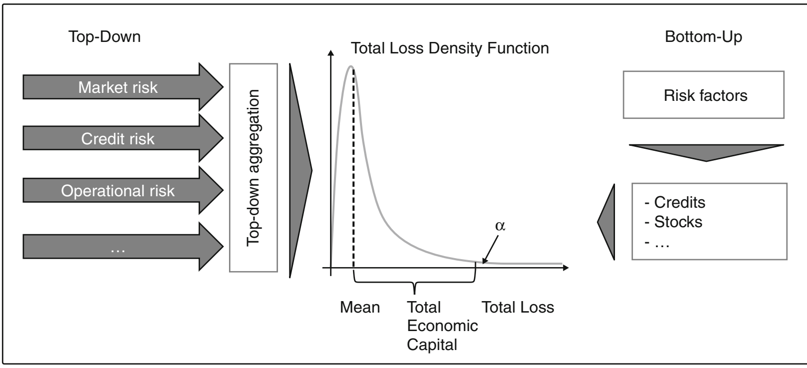

Figure 9.5 Integrated economic capital: top-down vs. bottom-up approaches

operational, and eventually other risks. Thus, we aggregate these risks through a given function in order to obtain the overall total economic capital. On the other hand, when we focus on bottom-up approaches, we start from risk-factor simulations and evaluate portfolio activities in order to compute the overall total economic capital.

The difficulties in implementing the top-down approach are, on the one hand, to choose the adequate joint distribution function and, on the other, to estimate parameters with the limited availability of loss data. Furthermore, as is evident from Kuritzkes et al. (2002), Dimakos and Aas (2004), Aas et al. (2007) and Grundke (2010), there is a problem in representing all interactions among risks through some parameters of a joint distribution function.

Kretzschmar et al. (2010), Drehmann et al. (2010) and Alessandri and Drehmann (2010) propose alternative bottom-up models to estimate the bank's economic capital.

Despite the interest in risk integration from both the regulatory as well as the managerial perspectives, the use of integrated models is not widespread among banks. From the research point of view, the above-mentioned papers attempt to establish how to catch the integration issue, but there are some problems that are far from being resolved. In particular, there are some risks that cannot be directly compared because they relate to different holding periods; a typical example is that market VAR is usually computed over ten days, while credit UL are computed over one year. In addition, the concept of capital is not always agreed on; for example, some people concentrate on the share value of the firm

while others consider the book value. Despite these issues, the risk integration process constitutes one of the most important challenges for the practice of risk management. This is particularly true in financial systems where there is a strict interaction among alternative risk sources.

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10
Portfolio Management

Tommaso Giordani and Corrado Giannasca

10.1 Introduction

A reasonable definition of risk management is that it is the organization of resources and technology that focuses on the finalization of a continuous forecasting action. Forecast actions are part of the preventive-action family that very occasionally provides evidence that the action would have been the best decision for the company.

Ultimately, credit risk management exists to minimize both impairment (credit losses) and capital consumption, and its objective is connected to the optimization of human capital through the competence model and the optimization of direct costs, as described in the table below. The capital perspective assumes a relevant role for advanced portfolios under BIS II, but for standardized portfolios, once profitability remains within company hurdles there are no specific optimization levers.

In more sophisticated banks, the credit risk department is also in charge of measuring the risk-adjusted profit and the decline (for each product) of the appropriate commercial prices for homogeneous clients or individual applicants. So even if the department's actions achieve the above objectives, we can argue that credit risk management primarily focuses on explaining how to develop predictive models for bad clients to improve collection efficiency or stress testing rather than explaining how to assemble these objectives within a unique framework. In other words, credit risk management seems to focus on how the car is built rather than on how the car should be driven.

The objective of this chapter is to contribute to improving the understanding of how credit risk managers might create a comprehensive framework to finalize the minimization of "surprise risk". The framework would help eliminate the internal risk of communicating to

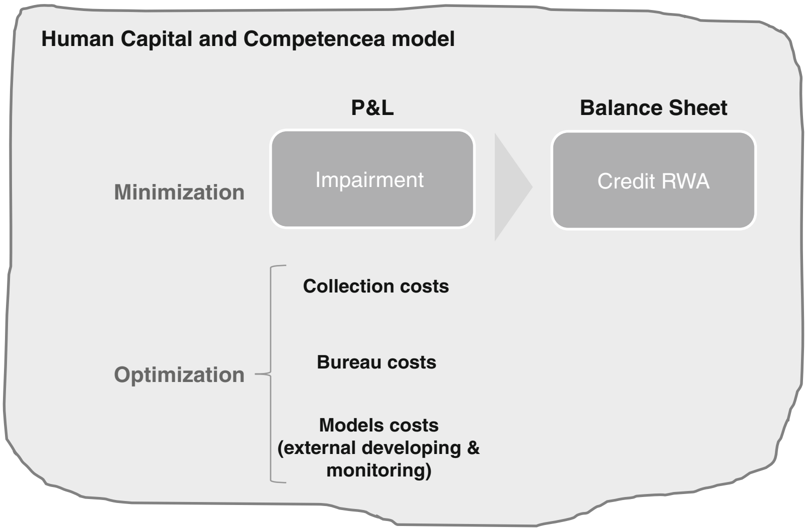

Figure 10.1 Portfolio management goals
Source: authors

senior management huge divergences in the yearly plan due to adverse events (internal or external) not factored into the plan, or significantly underestimated, that affect yearly profitability targets.

10.2 Team organization and competence model

What are the human capital characteristics and the competence model that the credit risk department needs, and in particular what are the "internal and external variables" that must be monitored?

Let's start with the human capital that, technology or no, makes the real difference in a successful risk management action. Model outcomes (application scoring, profitability, roll rates) without a robust control framework and without a continuously challenging approach can result in nasty surprises. In the current spreadsheet era it is human capital that represents a real line of defense against such surprises.

A quantitative background is certainly preferable, but assuming appropriate numeric capability the portfolio management team should primarily be composed of enquiring but cautious people. Whatever form credit risk management takes, the management team needs to be able to answer the following three questions at any given moment:

	Where we want to go	What we have to do	Where we are
Credit	Collection Strategies Modelsteam	MI team	Portfolio managementteam
Suppliers	Collection ops.	Company DWH	MI team
Clients	Planning (CFO)	Collection Strategies Models team	Sales Operations (COO)

Figure 10.2 Portfolio management team radar
Source: authors

The inclusion of suppliers and clients is not accidental. One of the key success factors for credit risk management is in fact represented by line managers' ability to have a close relationship with these stakeholders.

Another topic that is often underestimated in credit risk management is a communicative approach that given the complexity of the topic is not intuitive behavior.

From a psychological perspective, we can say that a risk manager should have some personal qualities that are often opposite to the usual behavior:

1. Don't think like someone who can forecast any possible event.
2. Don't focus attention on what you already know.
3. Don't make decisions always based on the more reasonable perspective (simply because it is easy to explain).
4. Don't be satisfied by confirmation of an initial hypothesis.
5. Don't focus attention on events with irrelevant impacts.
6. Maintain a medium- to long-term memory.

10.3 Portfolio management cycle

What are the credit risk variables (external and internal) that must be forecast and monitored? Let's try to identify a basic scheme in the figure below:

Portfolio management can be split into three different areas. The first is EPM, that considers the portfolio's vulnerability to the economic cycle,

Figure 10.3 Risk appetite cycle
Source: authors

collection efficiency, strategy effectiveness, and the potential impacts from new model (application, impairment, capital) development and the calibration of existing models. Each of these components needs to be mitigated by managerial actions. The second area relates to new business planning. This looks at the client segment that is considered strategic for the bank, the pricing strategy for the client, the acceptance strategy consistent with the risk profile of the existing portfolio, and ultimately with the profitability target. The third area is relative to the punctual monitoring of the divergences from the key objectives embedded in the plans. Portfolio management in reality starts with a robust forecasting exercise.

Reactive rather than preventive risk management results in an inability to control the P&L and the cost of risk. Above all, it exposes the bank to sudden unexpected events without leaving sufficient time to implement identified corrective actions (surprise risk). A rigorous forecast plan, however, not only identifies potential risks but also the managerial actions that mitigate the adverse impacts arising from those risks.

10.4 Existing portfolio management

Existing portfolio management consists of the activities illustrated in Figure 10.9.

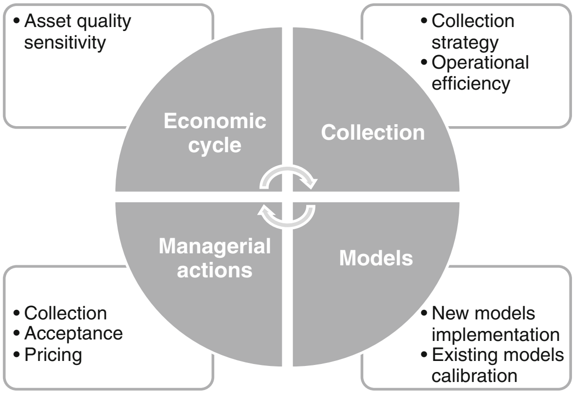

Figure 10.4 Existing portfolio management
Source: authors

Impairment and Risk-Weighted Asset are ultimately connected with the four blocks reported above. The determination of the portfolio's sensitivity to the economic cycle, particularly during a downturn, represents a crucial exercise carried out during the yearly planning and has to be periodically refreshed. The collection strategy can significantly change from year to year because of internal and external factors such as implementation of a new system or new regulatory requirements (such as a tightening of controls or new "Treat Customer Fairly" requirements). In addition, the senior management's objective of optimizing the bank's costs can present some additional challenges to the collection department that might worsen collection performance and therefore result in impairment. Moreover, models adopted to calculate impairment (BIS II advanced risk parameters or other methodologies) under a PIT (point-in-time) perspective should be periodically refreshed to provide one-off impairment impacts that should be factored into the yearly impairment plan. Whichever approach is selected, the time required to design, gain approvals and implement the appropriate actions takes precious time from mitigating the adverse impact; for this reason, a contingency plan needs to be developed during the planning phase to identify the extra investment eventually necessary in terms of internal resources or collection agencies' costs.

10.4.1 Economic cycle

Conditioned by asset population characteristics, bank portfolios might show a higher or lower sensitivity to changes in the macroeconomic

scenario. In particular, stress testing techniques have recently been developed to verify capital adequacy. From a retail banking perspective, the starting point for these stress tests is to identify the relation between macroeconomic KPI (GDP, Unemployment rate, HPI) and asset quality, especially with 0–1 roll-down KPI (which highlights on a monthly basis the number of new clients that have missed installment payments).

A sophisticated stress test approach foresees the use of different macroeconomic KPIs contemporarily that define a comprehensive scenario (such as the Euro break-up). But this approach implies the study of the correlations among the several macro KPIs utilized and the target variables that makes the model exceedingly complex by introducing significant issues related to the model's back-testing (Ashish 2004).

Experience shows that the most important macroeconomic factors for retail loan portfolios are unemployment rates and changes in house prices (Breeden and Lyn 2008). By looking at the distribution of the logit transformation of the unemployment rate or the log of the ratio of levels of nonfarm payrolls year over year, we can obtain a good proxy for understanding long-term variation in the environmental factor, Yt. The longer the available historical series, the more robust the correlation outcome (calculated through a logistic regression).With respect to recently developed approaches (Breden 2008)that study delinquency ratio correlations as the environmental factor, we suggest the use of the 0–1 roll-down factor because this approach reduces "noise" coming from the delinquency portfolio that stayed in this status before the variation of the selected macroeconomic KPIs.

Ultimately, the managerial question to be answered is this: How much does the 0–1 roll-down increase due to certain variations in the unemployment rate? In practice, the answer is the relation between a deterioration (improvement) of the macroeconomic environment and the yearly total impairment amount forecast on the basis of the recent collection performance and the new recruitment risk profile. The final goal is to identify warning levels of macro KPIs that can jeopardize the attainment of the target. In case of trigger breach, managerial actions already planned can be activated.

The overall basis of the stress level is not important, but it is essential to link this stress with specific portfolio segments. So it becomes necessary to analyze the specific concentration. Figure 10.6 gives the more vulnerable segments based on our experience.

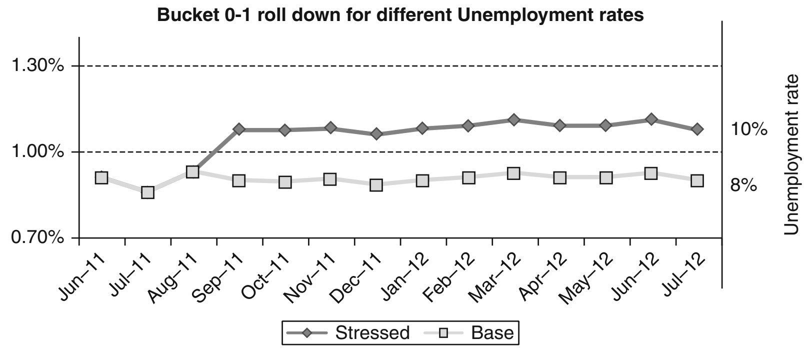

Figure 10.5 The 0–1 roll down correspondent to different unemployment rates
Source: authors

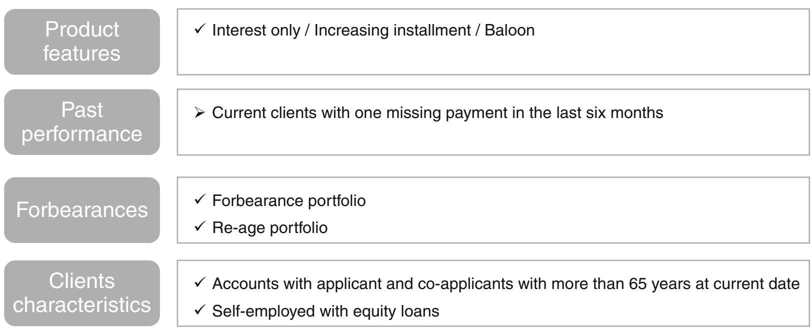

Figure 10.6 Portfolio vulnerable segments to economic cycle
Source: authors

10.4.2 Collection performance

For retail portfolios, collection performance can be represented as a multidimensional strategy where timing, target and cost represent the three dimensions to optimize.

Figure 8.7 clarifies the main challenge faced by collection managers every day and that, above all, they try to factor into their yearly planning.

We cannot walk through the characteristics of good collection reporting, but we can highlight what is essential to disclaim when explaining how the collection effort supports the achievement of the planned impairment figure and the level of the cost optimization.

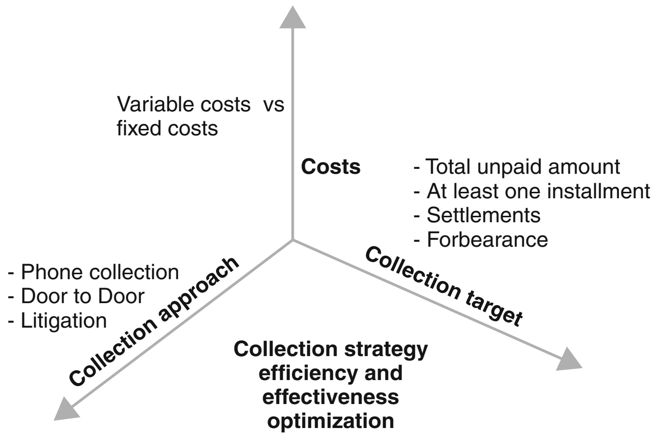

Figure 10.7 Collection strategy dimension
Source: authors

10.4.3 Models

The risk parameter adopted to calculate the impairment (PD and LGD) through whatever methodology the bank adopts should be monitored on a quarterly basis and refreshed taking into account the shifted fixed-term window (that is, the previous 12 months).

Collection effectiveness and sensitivity to the economic cycle have a straightforward impact on portfolio asset quality, and with a certain time lag the development sample of application, behavioral, and impairment models both in terms of stability and mode accuracy. Sometimes, the influence is so great that a new model needs to be developed, or recalibration may become mandatory. Focusing our attention on impairment parameters adopted by the bank, the yearly forecast has to take into consideration how changes in the asset quality determine variations in PDs and LGDs. In short, a yearly model plan should be defined, where each model implementation or refresh that has an impact on impairment can be determined.

10.4.4 Managerial actions

In order to mitigate surprise risk, an action plan should be delivered and possibly approved by management committees. These action plans can be divided into three categories as shown in Figure 10.8.

Cut-off and pricing actions will be discussed later, so we can now focus our attention on collection actions. In practice, collection actions

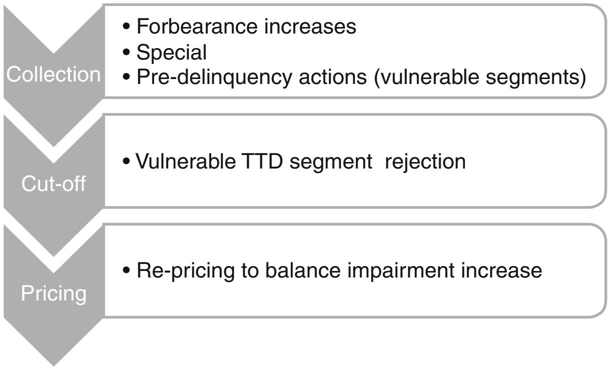

Figure 10.8 Managerial actions
Source: authors

other than those already factored into the yearly plan are called pre-delinquency portfolio management. In other words, these actions involve direct contact with clients with a high likelihood of non-payment in the short term.

10.5 New business portfolio management

With regard to the new portfolios, the most important element is the bank's ability to calculate lifetime profitability for each portfolio and portfolio segment. From that calculation, a lending strategy can be defined that represents the bank's risk appetite and profitability.

10.5.1 Profitability and pricing

Risk–reward models are statistical tools that forecast the profitability of new lending over a defined period of time and/or over the expected lifetime at segment level. Segments should be selected based on a high correlation with profitability and/or customer behavior. For the purpose of defining lending strategies for new business lending, at least two profitability return measures should be used:

$$\textit{Economic profit (EP Lifetime)} = PV\ (Pat) - [PV(\textit{Absorbed capital}) * \textit{Hurdle rate} \tag{10.1}$$

$$\textit{Return on Risk-Weighted Asset (RoRWA lifetime)} = PV\ (Pat) \,/\, PV\ (Rwa) \tag{10.2}$$

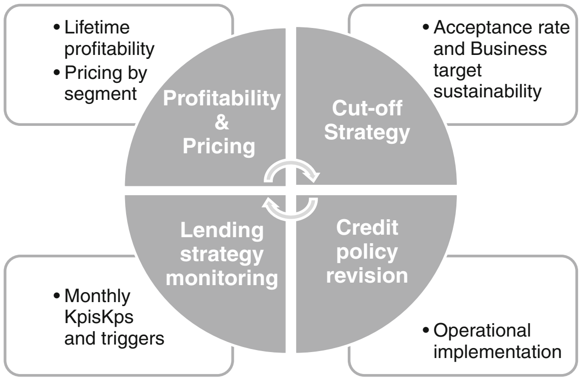

Figure 10.9 New Business portfolio management cycle
Source: authors

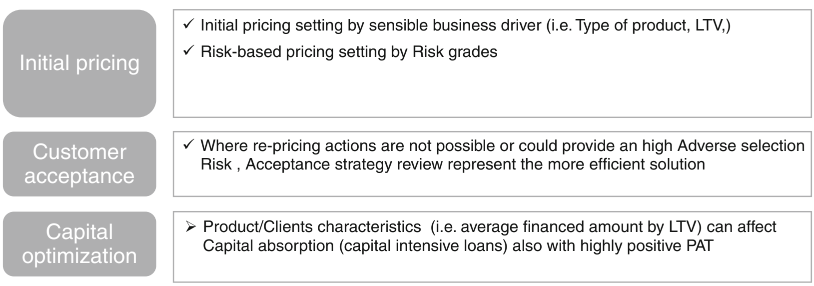

Figure 10.10 New business portfolio management
Source: authors

All averages in numerators and denominators of the calculations should be over the expected lifetime of the asset (minimum five years forecast time horizon). For AIRB portfolios, the RWA measure should be based on the total regulatory expected loss and should incorporate the expected loss deduction element, which might be positive or negative, of the expected loss calculation. The risk–reward models contribute to defining the lending strategy. Table 10.1 shows the three main goals of the strategy.

The risk-adjusted profitability measures allow the connection of the results with the risk assumed and the monitoring of the specific business unit; this results in an increased awareness by the sales department of the creation of company value rather than allowing their attention to be focused on maximizing the lending amount only.

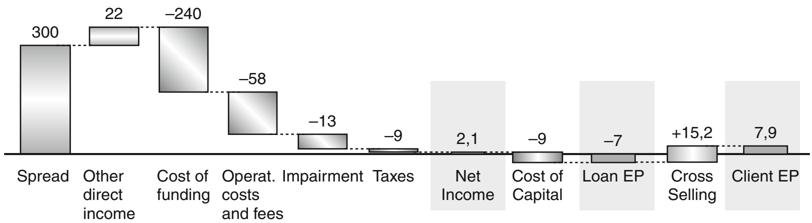

Figure 10.11 Lifetime profitability build-up
Source: authors

The measurement of the profitability of a stand-alone product with an appropriate price setting is the first step to achieve. After that, the "client embedded value" perspective can make a valuable contribution to setting the company's strategic view. However, "client perspective" is not advisable if the answer to any of the three following questions is negative:

1. Is the marketing analytics team strong and does it provide good reporting around the analysis of the sensitivity to the take-up and price response ?
2. Does the bank sales strategy clearly describe the synergies around credit products as for X-sell action, particularly with respect to client segments?
3. Is specific P&L coming from X-sell activities in place and signed off by finance?

Without the simultaneous achievement of the three conditions above, the client's profitability perspective should not be seriously considered.

It is important to bear in mind that by "price" we are not only considering the interest spread offered to the client, but also all the financial conditions that ultimately affect the profitability of each single loan (that is commissioning, broker fees, loan amount and length, and level of collateralization). A pricing model should identify the profitability contribution of each decisional lever; pricing optimization should represent in the short term a variation of the credit spread offered to the client, but in the medium term, the research of an optimal combination of all the profitability components.

Risk-based pricing approach represents a maturity element in the lending market. Risk-adjusted price identifies the price that is able to guarantee target profitability in the medium- to long-term.

10.5.2 Cut-off strategy

Once the defined target profitability of each loan or client is determined, senior management has to choose the implementation approach by picking from the main strategic objectives of the bank: profitability maximization, capital allocation minimization, or asset liabilities optimization.

The necessity to prioritize these three objectives determines how senior management will decide to implement pricing strategy.

Usually, this kind of decision affects the specific objectives assigned to business, risk and finance directions. Hence, to facilitate symmetric information, a dedicated pricing committee is generally created.

The cut-off strategy ultimately means identifying the maximum lifetime risk that is acceptable (identified by client rating or scoring band calculated by an application scoring). The strategy does not significantly contribute to an increase in the average pricing standard deviation where the average pricing is in effect nothing more than the bank's business card. The card allows the market to identify the segment in which the bank has decided to operate. To define the more efficient cut-off requires the calculation of the average profitability by client risk rating, as shown in Table 10.1.

The calculation should look at recent recruitment to be consistent with the market environment. This kind of analysis permits the definition of an efficient boundary between cumulated profitability and volumes.

The final decision will be to reject or re-price each segment, and in this phase the portfolio manager's role is fundamental to the identification of potential adverse selection effects. In Figure 10.12, a pre-pricing

Table 10.1 Lifetime profitability by the client's risk rating

	Return on RWA									Re-pricing
Rating	Year1	Year2	Year3	Year4	Year5	5 Years avg.	Life time	% of Booked volume	Rejection rate	Δ bps on APR
1	33.39%	3.69%	2.18%	4.92%	4.08%	9.99%	9.19%	1.93%	3.00%	-
2	19.13%	5.09%	1.65%	1.70%	1.08%	5.06%	5.75%	6.67%	5.00%	-
3	6.32%	1.99%	0.84%	3.89%	3.56%	3.39%	4.17%	7.87%	10.00%	-
4	4.37%	2.01%	1.27%	1.47%	2.92%	2.66%	3.53%	6.85%	15.00%	-
5	4.42%	1.70%	0.59%	1.18%	0.24%	1.68%	2.27%	6.05%	18.00%	-
6	3.07%	1.13%	0.49%	1.85%	0.41%	1.45%	2.07%	4.89%	23.00%	20
7	1.94%	0.63%	0.21%	1.42%	1.68%	1.14%	1.61%	4.39%	38.00%	50
8	1.78%	0.31%	0.26%	1.25%	1.33%	0.96%	1.45%	3.32%	75.00%	70
9	1.27%	0.15%	-0.08%	0.65%	0.57%	0.58%	0.82%	0.39%	85.00%	90
10	0.27%	-0.10%	-0.12%	1.32%	1.26%	0.17%	0.42%	0.11%	90.00%	110

Source: authors

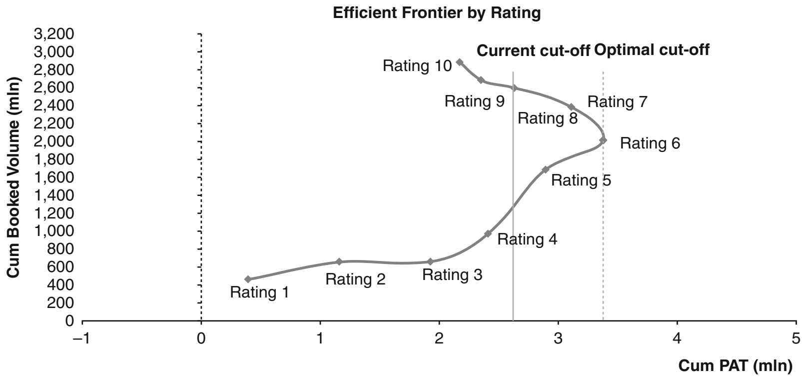

Figure 10.12 Efficient frontier by client's rating
Cumulated PAT by rating vs. cumulated booked amount - acceptance rate strategy objectives without re-pricing action
Source: authors

action of an 8 or 9 rating should be evaluated with attention under this perspective.

10.5.3 Credit policy revision

Once the pricing and cut-off strategies are in place, the next challenge is the implementation of the new strategy, usually within a credit-decision engine. This phase is essential because without an appropriate implementation test plan, the risk of making wrong decisions is very high. Moreover, a re-pricing action affects clients' affordability and eventual rating distribution (if factored into the application scoring model). The decision (for mortgages in particular) to enforce manual assessment is crucial to understanding the client's indebtness sustainability. The application of a flat affordability measure (such as debt to income or indebtness index) is reasonable only in the cases where prices have been relatively stable in the recent past, so that it has already been possible to evaluate risk performance (in particular through early delinquency KPIs). The psychological components behind indebtness to be taken into consideration are (Kahneman and Tversky 1979):

a Should not consider that the personal situation can change.
b Should not excessively rely on income coming from the elderly part of the family nucleus.
c Should not overestimate future income increases.

10.5.4 Lending strategy monitoring

Last but not least, all the relevant KPIs that can influence the rating distribution (variables factored in scoring models) or changes that arise in the risk profile of the clients should be specified and monitored individually. Monthly monitoring should be split into at least four areas, as described in Figure 10.13.

Consistency in the business strategy is crucial, and it is also crucial to have at least a monthly meeting with salespeople to understand if relevant changes are occurring. A point frequently underestimated is the TTD (through-the-door) profile from the scoring variables perspective. Credit risk management in fact does not usually share with the bank the variables factored in the application scoring. However, this behavior is a mistake unless the organizational structure or a lack of an appropriate a data quality-control framework does not indicate the opportunity to avoid this sharing. Apart from the two conditions above, ignorance in the business side of the main criteria on which applications have a basis is always an error that creates:

1. Disconnection between the bank's risk appetite and front-end targets.
2. Time consumed (wasted) by network to create a relationship with clients out of risk target.
3. Costs increased (bureau costs among others).

An example of a lending strategy dashboard is represented in Table 10.2.

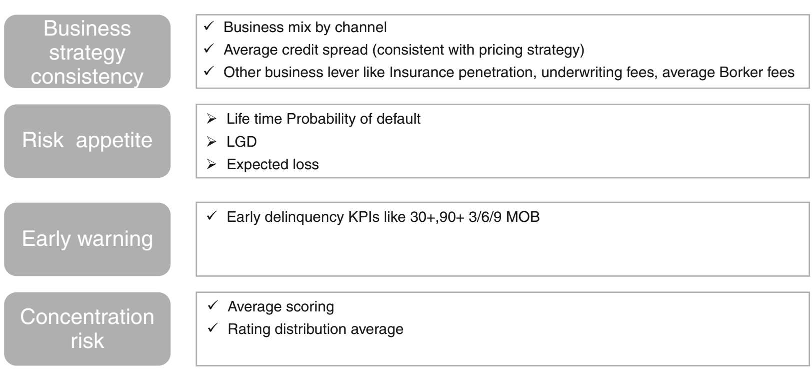

Figure 10.13 Lending strategy monitoring areas
Source: authors

Table 10.2 Lending strategy monitoring areas

Sezione	KPI	Trigger	Trigger	D	J	F	M	A	M	J	J	A	S	O	N
Business strategy consistency	Booked volume (#)	2,800	Greater	2,971	1,774	2,009	2,679	2,416	2,937	2,954	3,444	864	2,646	2,641	4,727
Business strategy consistency	Monthly Booked volume (€)	400,000	Greater	415,312	240,609	270,036	357,491	327,220	396,703	398,583	477,897	112,344	355,280	367,735	666,428
Business strategy consistency	Channel: Direct	50.00%	Greater	51.00%	52.30%	48.00%	47.60%	49.00%	51.50%	49.50%	49.40%	48.30%	43.60%	42.50%	41.00%
Business strategy consistency	Channel: Top broker	15.00%	Greater	15.00%	16.40%	18.20%	19.40%	12.20%	15.00%	14.00%	14.10%	14.30%	16.90%	17.00%	18.40%
Business strategy consistency	Channel: Remote	35.00%	Greater	34.00%	31.30%	33.80%	33.00%	38.80%	33.50%	36.50%	36.50%	37.40%	39.50%	40.50%	40.60%
Business strategy consistency	Insurance penetration	85.00%	lower	70.18%	73.74%	80.05%	85.78%	88.01%	90.13%	91.14%	90.85%	89.24%	86.46%	80.26%	68.92%
Business strategy consistency	Average spread	1.60%	lower	1.58%	1.63%	1.64%	1.60%	1.59%	1.65%	1.68%	1.70%	1.69%	1.71%	1.73%	1.75%
Acceptance strategy	Acceptance rate	62.00%	Lower	70.19%	69.88%	62.15%	69.66%	66.45%	69.03%	67.60%	63.07%	62.43%	68.76%	70.76%	56.76%
Acceptance strategy	Override	2.00%	Greater	0.70%	0.96%	0.55%	0.26%	0.29%	0.17%	0.40%	0.41%	0.61%	0.22%	0.39%	0.06%
Risk appetite (RR model input)	PD at 5 years	1.00%	Greater	0.85%	0.85%	0.86%	0.87%	0.86%	0.85%	0.85%	0.84%	0.80%	0.80%	0.80%	0.80%
Risk appetite (RR model input)	LGD at 5 years	38.00%	Greater	38.24%	38.33%	38.53%	38.46%	38.60%	38.44%	38.65%	38.56%	38.45%	38.36%	38.65%	38.70%
Risk appetite (RR model input)	Average EL	0.40%	Greater	0.33%	0.34%	0.34%	0.34%	0.34%	0.33%	0.34%	0.33%	0.31%	0.32%	0.32%	0.32%
Early warning	30+ 3MOB (%)	0.10%	Greater	0.01%	0.10%	0.03%	0.00%	0.05%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.15%
Early warning	30+ 6MOB (%)	0.58%	Greater	0.27%	0.11%	0.30%	0.11%	0.10%	0.26%	0.17%	0.02%	0.16%	0.00%	0.17%	0.15%
Early warning	90+ 12MOB (%)	0.86%	Greater	0.57%	0.37%	0.70%	0.72%	0.60%	0.34%	0.49%	0.29%	0.36%	0.19%	0.17%	0.26%
Early warning	C/O 12MOB (%)	0.36%	Greater	0.00%	0.00%	0.00%	0.00%	0.06%	0.00%	0.00%	0.01%	0.00%	0.00%	0.00%	0.00%
Concentration risk	Average scoring	415	Lower	414.7	414.3	413.8	413.4	413.4	414.3	414.3	414.8	416.0	416.4	416.2	416.3
Concentration risk	High Risk	0.2%	Greater	0.40%	0.43%	0.50%	0.10%	0.08%	0.06%	0.17%	0.09%	0.35%	0.14%	0.12%	0.00%
Concentration risk	Medium Risk	6.4%	Greater	4.50%	4.87%	5.09%	5.16%	5.40%	4.78%	4.43%	4.33%	3.70%	4.01%	3.74%	3.78%
Concentration risk	Low Risk	91.3%	Lower	95.10%	94.70%	94.41%	94.74%	94.52%	95.16%	95.40%	95.59%	95.95%	95.85%	96.14%	96.22%

Source: authors

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Part IV
Operational Implications

11
IT Systems for Credit Risk Management

Renzo Traversini and Anselmo Marmonti

11.1 Introduction

In this chapter, we describe the general characteristics of IT Credit Risk Management systems. The scope of these IT systems that are part of the wider IT infrastructure of the bank comprises its entire credit cycle (see for instance Basel Committee, 1999). Key activities of the cycle to be supported are:

(1) Risk taking, that in the case of banks comprises commercial banking activities, all lending activities that address the different segments of the bank's customer base, and credit risk exposures connected to trading activities.
(2) Risk management, that covers the activities a bank sets up to classify the exposure, determine the creditworthiness, measure the risk components, analyze the individual and overall risk situations, diagnose the critical situations, and design and activate counter-actions.
(3) Risk mitigation, referring to how the bank manages and monitors risk mitigation activities.
(4) Risk pricing, covering how a bank links credit product pricing to creditworthiness, profitability and impact on overall economic capital

The IT systems that we refer to are aimed at automating information processing, streamlining credit process execution, and supporting decision making in all the four areas above.

Usually, IT systems that manage the lending approval processes are not just a part of the credit risk management; they are a more generalized part of the operational infrastructure of the bank. These systems are part of the process of credit risk management because they provide

the environment where, during risk-taking activities, the collection of all original data regarding the assessment and evaluation of individual credit positions takes place. The credit risk management system interacts with this operational layer during the credit approval process (and during the credit reevaluation process) to provide, for every single exposure, a measurement of all risk components that are involved in the approval process.

To simplify the overall picture, we can consider that the operational IT system supports interaction with the credit process by means of a risk engine that belongs to the credit risk management system. This interaction provides the necessary risk information during the approval or revision of credit positions. The risk engine is the connection component between the credit risk management system and the operational layer of the bank's IT system.

In addition to the risk engine, there are several macro-components that are required to set up the credit risk management system. Below, we consider the most relevant components and their specific characteristics.

11.2 Credit related information – CDW (Credit Data Warehouse)

The basis of a solid credit risk system is the availability of the necessary data required for the analysis and evaluation of the counterparties (Bhatia, 2006). The process of data collection and organization is quite complex and intensive due to the large spectrum of different types of data required. The data are specific for any business segment of a bank, such as retail, small business and corporations. As a matter of fact, a large proportion of the relevant institutions feels that the level of the current data management for risk management is not completely effective to date (Deloitte, 2011). Moreover, the risk-modeling activities require quite a wide set of additional information connected to both master and financial data of the counterparties with an adequate time-series span for a proper statistical analysis (Varetto & Szego, 1999).

In real-world situations, a large part of this data is already available in the internal IT system of the bank, in particular for the set of the bank's current customers, while the remainder must be collected by a data acquisition process that relies on external providers. Recently, most banks have set up structured credit data warehouses with a development roadmap focused on an increasingly wider collection of data to cope with a more granular and precise analysis of the counterparties'

creditworthiness. Such a wide scope of IT programs currently faces two critical issues, as follows.

11.2.1 Information quality management

The parallel focus is on the quality of the data that initially is quite low due to the many systems with different data designs and usually without a sufficiently wide time series. The quality of the information regularly processed for the purpose of credit risk is currently a key aspect addressed by supervisors in the validation of the credit risk management systems (Basel Committee, 1999 and 2006; Bhatia, 2006).

To ensure that the credit risk process can take place coherently and to prevent inefficiencies due to the lack of accuracy and completeness of the available data, a specific information quality management system should be put in place as an added component to the CDW. The relevance of this subsystem is not only related to the adjustment of input information to credit processes, but also as a feedback tool to operational systems to allow for continuous improvement of the operational risk processes.

11.2.2 Master data management

To enforce quality management and to align credit management processes with other internal processes, there is a strong need to centralize and make unique all of the sources of anagraphical and descriptive information on items related to credit such as customers, products, and organizational components.

11.3 Models for risk components – the development environment of internal rating

The ability to set up and manage an advanced internal risk-modeling activity has become more and more of a strategic asset for banks (Chu et al., 2007). The macroeconomic changes and their impact on the counterparties show that the capability of an institution to obtain the correct estimation of the credit quality of its own counterparties and the capability to timely calibrate or estimate the model are fundamental to react to external changes and to build a competitive advantage, properly value the risk, and define the right risk-adjusted credit policy.

Best practices for the internal rating model are currently aimed at a better evaluation of the specific characteristic of each segment of the portfolio to bring about a more comprehensive analysis of the behavior of each counterparty through the economic cycle and to a point in time (Siddiqui, 2005; Chu et al., 2007).

For the purpose of gaining the mentioned competitive advantage, risk departments need a flexible laboratory environment that allows the bank's analysts to timely develop and monitor their own models with a strong autonomy that avoids impacting the IT department. Most analysts have a range of specific analysis libraries (Deloitte, 2011) due to the wide variety of possible approaches, from the purely statistical to cash flow Monte Carlo simulations. These libraries allow the analyst to design a model and test its performance by a graphical interface (Chu et al., 2007). Hence, this model is something that also helps to produce documentation of the method used and easy interpretation of the results for internal purposes (development team, internal audit, and internal review) and for external interested parties (financial markets and regulators).

11.3.1 Model management and model deployment components

The model's management component allows the institutions to govern its life cycle: model development (Banca d'Italia, 2006; Bhatia, 2007), validation (Basel Committee, 2005), application in the credit process (Chu et al., 2007), monitoring of the performances (Chu et al., 2007), and maintaining / archiving of the models when their predictive powers fade.

In the past, banks did not use to focus on these aspects, but now the growing number of models (Chu et al., 2007) and the rising frequency of model updates make this activity a priority for IT departments. An efficient model management process (Chu et al., 2007) must also be based on an optimization of costs and the time required for the management of the model base. Usually a particularly critical phase is the deployment of the models developed in the daily business process that requires an exchange of information between the risk and IT departments for proper and timely usage. The current evolution of the technology allows a high level of automation in the management of this phase to minimize the impact on the risk management in terms of documentation, and on the IT department as well in terms of applying the new model in the credit process. For example, the credit process includes evaluation of the credit risk and the risk-adjusted pricing for new potential customers.

11.3.2 Credit portfolio valuation and management system

The availability of reliable EAD, PD, and LGD measures allows the banks to evaluate and manage their credit portfolios properly. These measures

are used as input for the modeling of the expected and unexpected loss for each counterparty at the portfolio level. There are many approaches like the standard and IRB risk-weighted asset that are based on regulatory rules and internal approaches like CreditMetrics and CR+ (Cossin and Pirotte, 2001). A proper system should allow the risk department to compare the results provided by different approaches and provide the capability to adopt the best model for each segment for a correct evaluation of single and correlated risks.

To properly face the changes in the economic contest and consequently to drive the credit policy, the credit portfolio management should be able to simulate the key variables of the portfolio by providing not only the current vision but also a process to evaluate the impact of the portfolio strategy in different economic and stressed scenarios.

On the other hand, the credit portfolio management system needs to have the capability to simultaneously produce both the official measures for the regulatory reporting and the internal measurements to radically minimize the time and costs of reconciliation.

11.3.3 Analytical information on credit risk – CR data mart

More and more, risk management analysis is producing a huge amount of data that requires adequate organization to be used efficiently. The availability of granular and detailed data is the basis for a proper analysis. The amount of detailed information that must be kept available online is becoming so huge that data cannot be managed by the traditional individual productivity tools but requires a structured data repository and a specific analytical system to cope with the complexity of the task. There are data referring to different areas, such as the customer master data, the risk components, the expected and unexpected loss, and the exposures, that are connected to the risk components; but there is also data regarding the collaterals, the guarantees and other information connected to the financial instruments side. Data is increasingly used in institutional processes such as Pillar 3 and regulatory reporting to the supervisor. Therefore, it has to be archived considering all the elements describing the analysis: the portfolio analyzed, the value of the risk factors, the analyses, and the underlying hypothesis. The banks usually have a multi-entity structure, and this structure is relevant for analyzing a single entity in the group context and to obtain a consolidated vision of the entire group.

11.3.4 Dashboard e-reporting

The dashboard and reporting part is one of the key components for the distribution and the proper usage of the credit risk information throughout the organization. Credit risk reporting can be classified broadly as regulatory reporting and reporting for internal purposes. The regulatory reporting component depends strongly on the requirements as defined by the local regulator. The basis settled by CRD directives can be largely broadened by those local regulatory requirements. Reporting for internal purpose generates a large demand for credit risk information throughout the entire organization. At the beginning, this reporting was more focused on the analysts of the credit risk department who managed the model details. But now that the credit risk is a central part of the banking business, the information is used in many different departments: the risk management department for an aggregated view of the risk exposure across risk; the financial planning and control departments for the risk-adjusted planning and evaluation of the performance; the credit department for monitoring portfolios and the definition of the credit strategy; and the top management for monitoring of the key ratio of the bank.

11.4 IT system to support credit risk management activities – key functional issues

An IT system that supports credit risk management activities should be designed, implemented, and delivered according to standard IT industry practices. These practices can be substantially different based on the type of IT system under discussion, with reference to the role of the system in the overall organization of the ICT services of a particular institution.

11.4.1 The general features of credit risk management systems

The general features of the credit risk management system can be grouped along a few basic conceptual subsystems:

1. The foundation of the credit risk management system must include a data layer prepared specifically for supporting the credit process. This part is a typical information base (or data warehouse) system (Basel Committee, 2006).
2. Part of the system is a pure business intelligence decision support system, using the above-mentioned data layer and functionally located over the existing operational IT systems (ERP and the like).

3. Other parts of the system are business user working environments (or “laboratory”) where non-IT people manipulate data, perform analysis, and produce knowledge to be transferred into the procedures of the credit risk management’s IT systems. These are the risk component models or credit portfolio models.
4. Part of the system is a change management environment where model procedures are managed according to the lifecycle of the risk model. The model can be promoted to or retired from production by an administrator.
5. A specific part of the system receives models in an executable form and makes them available in the risk engine that produces risk information for the credit processes.

According to these generic guidelines, the key functional issues to focus on when designing and building the credit risk management system can be categorized as follows: data management, information management, and data quality requirements (point 1 above); requirements linked to individual risk component modeling (laboratory environment and model development – point 3 above); functionalities to support the lifecycle management of the risk model (model management and model deployment – point 4); requirements related to portfolio risk modeling (as in point 3); business intelligence functionalities (dashboarding, performance management, and decision support – point 2); and general compliance with Basel II requirements (all points, including point 5).

Data management, information management, and data quality requirements

Data management is the ability to automate the full data collection process needed to create and maintain the risk information base. Information management is the assessment and monitoring of data quality in the risk process. The data quality is the management of business-defined data quality rules for their development and for moving rules to execution.

Individual risk component modeling

The user’s working environment should be aligned with the technical skill and practice of knowledge workers operating in the field of statistical modeling (for internal rating risk components) and stochastic financial modeling (for portfolio modeling). There is a strong need for user-friendly environments where complex step-by-step modeling processes should be possible. A comprehensive set of data validation, data

transformation, variable selection, dependence modeling and assessment techniques should be available and constantly updated. The user's work-in-progress and overall analytical by-products should be maintained, documented, and made available to the community of users. At the end of the model's development activity, the user should be able to collect in a single managed object all the elements that determine a specific risk model, including sample data used for model fitting, the entire statistical process from the input sample data to the final output of fit steps, model parameter values and initial model performance indexes, test statistics, and other evidence that support modeling choices made in the course of the model development process. This "model" object should be the base for non-subjective documentation of model development activities, and support the validation of the model. Moreover, the system should be able to interpret the model's structure and create the IT procedure that calculates model output given inputs and parameters. The model's procedure should be created in a way that minimizes any need for further verification before entering into normal usage.

Lifecycle management of the risk model

Management should be capable of managing approval checks and stating transitions of models. It should also map the model states, eligible transitions and validation checks with connections to the organizational function involved. Management includes monitoring methods to generate alerts and intervention signals by using Basel II guidelines as the minimum requirements.

Portfolio risk modeling

This model contains all of the widespread portfolio risk calculation methods as from the literature (CR+(TM), CreditMetrics (TM), KMV (TM), …). It has the possibility to modify or integrate a single method by directly adding functional aspects and to execute the calculation in different running modes such as batch, interactive or what-if simulation. The model also has reasonable performance of the calculation execution to allow the practical feasibility of specific applications.

Business intelligence functionalities (dashboarding / performance management /decision support)

These functionalities comprise a wide range of functionality in defining monitoring and publishing risk KPIs. They are a library of definitions and hierarchies that can be used to speed up the definition of system output

processing and reporting. Dashboarding is report building functionalities at user level. Performance is forecasting methods that can reach a reasonable prediction precision in anticipating trends in KPIs. Decision support comprises full management of KPI operational limits, alarm setting, issue notification, and action plan management. It also presents the possibility to represent and store risk strategy concepts with reference to risk KPIs under monitoring. In addition, it evaluates strategy check functionalities and the availability of predictive performance management concepts.

General compliance with Basel II requirements

According to the published directives and guidelines, several of the functional issues described above are included in the scope of Basel II norms. Those norms are basically oriented to let each institution be independent in the implementation of a credit risk management system provided that every aspect of the system that results from the design decisions is explicitly motivated by the institution based on factual evidence and a conservative subjective approach. The institution has a full awareness and control of the internal logic and structure of the system. Some of the general features of each subsystem should be assured, in particular: full documentation, auditability, reproducibility of risk calculation and outputs given a specific input, completeness and coherence of every decision process, and in general the evidence needed to support use tests.

These requirements are then a sort of general framework that includes all the previous specific issues and lets the system be considered as aligned to the vision inherent within Basel II. The local regulator, then, has given and in-depth interpretation of the framework better defining or restricting the functional aspects related to Basel.

11.5 IT technologies for credit risk management – key aspects

In an ideal situation, the credit risk management system is designed, implemented, and delivered from scratch by using IT technology specifically identified, purchased, and integrated into the overall IT system of the bank. In this perspective, the set of key functional issues listed in the previous paragraph should be considered important items to be evaluated when considering the different IT solutions and technologies available in the market.

The real-world experience departs from this ideal case because of the different make/buy mix level the IT department in different institutions

is set for and the pre-existing set of IT assets available in the institution and eligible for use. However, the possibility of adequately fulfilling the key functional requirements of credit risk management must be supported by IT solutions that bring to the institution (or are already providing) specific technical values to enable the proper support of the target architecture.

11.5.1 Data management and data quality – warehousing technologies

Data management technology has the capability to access many data formats in an efficient way. This accessibility is a key aspect due to the many source systems where the data is usually stored. At the same time, the capability to verify the quality of the data acquired by the different systems regarding technical aspects (completeness of the data) and business content (reconciliation with balance sheet values) is relevant. In the context of data quality, fundamental requirements are the cleaning and the certification of the data. The current evolution of data management technologies allows the centralization of the checking rules and an easy interaction between IT and risk management departments to design new rules and continuously improve the quality level of the data, as required by the Basel II accord. Other relevant capabilities of the data management are: (a) the capability to design the transformation to be applied to source data to obtain the information requested by the different steps of the process (see Svolba, 2006); and (b) the capability to manage a workflow for a complete control of the process and a detailed assignment of the responsibilities to specific users and departments. In particular, due to the complexity of the processes and the numbers of departments involved, the capability to manage the workflow is fundamental for a correct and efficient production of the information (for example, data for regulatory reporting) and to contribute to or validate the final results. The documentation and auditability of all these aspects have to be guaranteed to respect the IT standard and the regulatory requirements. To this purpose, an advanced definition and usage of the metadata is required that allows complete control of the system, assuring high flexibility for the IT and business departments to face daily activities.

11.5.2 Modeling environment

The best practices in this area have made strong advances in the last ten years; currently, some approaches are consolidated and new ones are coming (See for instance Chu et al., 2007). For these reasons, the

key aspects of a modeling environment are methodology-driven tools, self-documenting tools, and model builders.

Methodology-driven tools make it possible for the analyst to define his or her own model by leveraging the features of an analytical environment designed to manage this kind of analysis and aligning with the Basel II requirements. These tools mean, for example, the capability to manage data-mining approaches based on the SEMMA[1] methodology or financial approaches based on Monte Carlo simulations for cash flows. These approaches use environments with specific functionalities to manipulate the data, and analytical and financial libraries to define the model, and they determine the parameters and test the performance of the model.

Self-documenting tools are highly relevant for many reasons. The methodological choices must be documented for both internal review and for the purpose of regulatory approval.

The development of the model requires teamwork, and the sharing between analysts of the analytical methodology and of the developed models is fundamental for an efficient process. The developed models are a strategic asset for the bank. Due to the high turnover of the analysts in the risk departments, a properly documented and structured model will guarantee the capitalization of the bank's investments. Model builders are usually a critical aspect of the capability of the modeling environment to build the procedure that could be used in the production process, for example for the evaluation of new customers. The evolution of the technologies allows the production of a model package that contains all the elements describing the model: data, metadata, methodological choices, performance tests, and the final model. This is a requirement for a proper archive of the model for future calibration but also for internal and regulatory reviews of the model. The automatic production of the procedure that can be applied by the production environment is the credit valuation process. This aspect is fundamental to the reduction of the costs and the risks connected to the rewriting of the scoring algorithm; experience confirms that automatizing this step reduces the time to market for a new model by three to eight months. In this case obviously the key point for a software tool is the range of formats that are automatically supported in the translation and that can then be used in production (such as C code, SAS code, Java, pmml).

11.5.3 Integration – platform approach

The management of the whole lifecycle of a model is usually a critical aspect, but the recent technological evolution can help the institution in this process (see Figure 11.1). The key capabilities of the model are

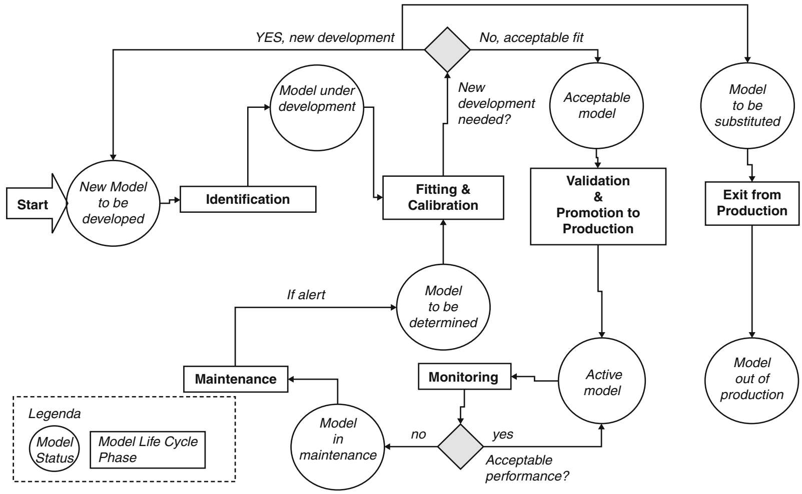

Figure 11.1 Internal rating model life cycle

the archiving of the developed models in a structured way with a guarantee of replicability in the future of the results and performance tests. Another capability is the deployment of the model to production with minimal manual activity. This aspect is fundamental for the integrity and replicability of the process. The main aspects of this deployment are the link between the model's data requirements, the data available in the processes, and the adoption of the best practices where the impact of this aspect are minimized. The possibility also exists to directly use a procedure generated automatically by the development tool. There are different approaches that could be used to minimize the impact of this issue. Some complexity arises when the model requires advanced analytics for processing (such as a Monte Carlo simulation). Deployment also involves monitoring the performance of the models (for example based on the BIS Working Paper 14) with functionalities for alerts in case of bad performance of the model.

11.5.4 The scoring engine

There are many aspects that must be considered for a scoring engine. The principal aspects are: the engine's purpose is first to evaluate a new customer or carry out a behavioral valuation. The engine should segment the portfolio into retail and corporate. It should also determine the IT

standard: host or departmental server. The current technologies are usually flexible enough to support different architectures, but there are some key points that must be guaranteed. The engine's performance is relevant both for the online evaluation of new counterparties and for the batch evaluation applying the behavioral models. The new technical capabilities in this area allow the usage of web services and high-performance computing to optimize both interaction with the front office systems and performance on the massive elaboration process. The engine's ability to simulate credit strategies especially for the retail segment is relevant to verify the impact of potential changes in the credit strategy. Also, the engine's coverage of the whole portfolio, especially the new models based on cash flow simulation, could require complex elaboration (such as Monte Carlo simulation) during an online valuation.

11.5.5 Portfolio risk engine

The portfolio modeling engine manages the complete and integrated analysis required for regulatory and internal purposes. The regulatory valuation by this engine is especially needed due to the current economic contest in which the banks are rapidly moving to internal modeling for the computation of regulatory capital. It requires an engine with the capability to apply not only the standardized approach but also the Internal Rating Based and advanced (IRBA) approaches. To face the requirements of Pillar 2 in Basel II, the engine must also support the portfolio simulation and stress testing. For internal valuation, the engine must be able to apply many models usually adopted for portfolio evaluation. On the one hand, the engine can use the customization of the regulatory models for a more bank-specific valuation; or on the other hand, it can apply the credit VAR model, the literature models (CreditMetrics (TM), CR+(TM), KMV (TM)), or have the flexibility to develop user-defined models.

Further evolutions of the models could be achieved with the support of advanced analytics. Algorithms available in some OR (operation research) areas can be applied to determine the best allocation of the collaterals to minimize the credit risk capital. A possible approach to this allocation focuses on minimizing the costs due to the haircuts requested; for example, to collaterals with a mismatch in the maturity or currency. The key points in this case are: (a) the flexibility in determining the objective function and the connected constraints; and (b) availability of high-performance computation facilities.

Experience shows that these advanced analytics have a relevant impact in minimizing the capital requirement.

Furthermore, the advanced analytics use the algorithms adopted in the operative research to determine the mix of the product that best fits the risk appetite and the expected performance target. The key points are the capability not only to add to the estimation the performance and risk measures but also to simulate the impact of internal strategies and of the change in the economic contest. Also needed is the capability to determine the risk-adjusted pricing. In this case, the risk adjustment should include not only the credit risk side but also other factors such as the cost of the liquidity risk. These features can help to secure for the bank a better integrated evaluation of risk and a reduction of reconciliation costs.

Dashboarding and PPM

The current high volatility of the economic contest is forcing several institutions to a higher level of monitoring and control of the risk exposures and a more efficient level of synthesis , to timely share the complex business dynamics with the board of the bank using a focused set of key information, allowing for better and faster decision making.

The key technological features are needed to achieve the following goals: strategic maps, strategy checks, and forecasting and early warning systems. Strategic maps allow the board to understand the current business situation by using specific key indicators and scorecards. Furthermore, the maps must have the capability to simulate at a high level the impact on the business due to specific actions on business drivers. A strategy check is the analysis of risk drivers and their correlations with risk performance. The previous two points are much more efficient if the valuation is based on coefficients estimated by robust analytical procedures that allow the determination of the relevant drivers and the correlations between the risk and performance. Leveraging the analytical capability makes a forecast of the risk and performance measurements possible. This leverage allows an efficient early warning system to be available.

11.6 Current status and trends for IT credit risk management systems

Over the last several years, Italian banks have focused their attention more specifically on the model development laboratory and on the data management process of the credit risk management system. All banks have already set up the overall credit management process along the

Basel II guidelines, and they are focusing their attention on the evolution of the system by aiming to increase control of the overall system and the performance of computation in the elaboration for a timely availability of the measures in the business process. They also aim to increase the performance of the models for a more precise valuation of the risk. Currently, the main priorities can be classified differently, based on a general segmentation considering the cluster of the large banks and the medium-size banks. However, the general issues listed above are still of general interest to all banks. To fulfill these requirements, banks are generally focusing their activities on several phases of the process.

The need to improve the quality of the data involved in the credit risk management process is particularly true for large banks that must consolidate data coming from many different information systems. The M&A activities of the past years make this issue particularly relevant and not easy to solve. Currently, all credit data are generally organized in dedicated data warehouse, and a set of controls is available to ensure a basic quality level. But the checks on the business content of the data are usually weak, and an overall data dictionary and repository of the data quality rules are lacking. This situation leads to a reduction of the efficiency in the controls with a non-uniform distribution of the controls and with a multiplication of checks on some areas that leave other data uncontrolled. In turn, these issues have a direct impact on the business due to the fact that a lack of data or the usage of wrong data impacts directly on the results of the internal rating models in terms of performance of models in the valuation of the creditworthiness of the counterparty and on the regulatory capital computed.

Reviewing current models to face the current economic contest is strictly connected to the process and the system available to the bank. The capability to calibrate or review a model and deploy it in the production environment by a structured system to support formal credit evaluation consistently reduces the effort required by both the risk management department and the IT department.

Completing the coverage of the portfolio is also important. In previous years, banks focused their attention on specific segments like corporations, SMEs and retail businesses. Now these segments are covered, and the priority is more on the other counterparty segments such as large corporations and banks. With the same purpose, the banks are extending their valuation to all the products, including specialized lending and the project financing. These valuations require a different approach, based on cash flow valuation and Monte Carlo simulation with a high impact on the systems in terms of computing performance.

Managing the nonperforming credits is especially important in the current economic contest because these credits are increasing both in volume and in size. For this reason, to maintain an equilibrium in cash flows and to reduce the cost of credit, the banks are activating systems able to evaluate the behavior of the customers, to produce alerts if the quality of the credit is fading, and to define the optimal operating strategy to maximize the recovered amount to minimize the cost of recovering the credits.

Improving the overall governance of the system is important for a more effective and efficient organization of the process. To face the necessity of delivering increasingly powerful models, the number of models is increasing and they are being updated more and more frequently. To maintain an efficient structure in terms of timely availability of the models and relative maintenance costs, the main banks are evolving their system to allow the risk departments to easily develop, calibrate and document the models. The usage of advanced tools help the analyst to develop better models according to the best practices by reducing the time required for the documentation as required by the regulator and to support the IT in the deployment of the engine to be applied in production. The last evolution allows the analyst to easily manage the version of the models for an automatic documentation and test of the winner.

The next issue is reducing the time required and the IT costs associated with the application in production of the models. The use of best practice helps the IT department by allowing direct execution in the production environments of the rules produced by the model development and by supporting the deployment in production of the updated model, thus minimizing the activities requested of the IT department. This issue also helps ensure the likelihood of replication of previous results according to regulatory requirements.

Defining a specific environment for the internal review of the models allows the internal review department to monitor and verify the assumptions and the performances of the models (see Figure 11.2). In this way banks can minimize the potential impact of errors in the development and application of the models. For the internal review department, the final evolutions allow a full valuation of the models and the monitoring of the performance in line with Working Paper 14 and the management of the validation process. In particular, the management of the process allows proper assessment of the overall quality of the models and the archiving of all elements required for an audit or regulatory control (Basel Committee, 2005).

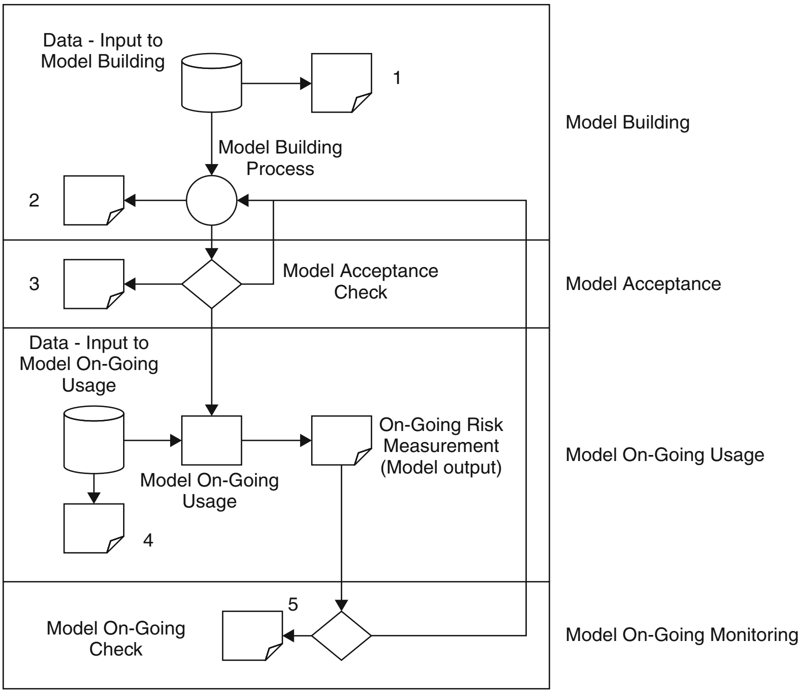

Figure 11.2 Basel II risk model validation concept

Relevant Check-point outputs:

1. Data (input to model building) – quality measurement.
2. Risk Model evaluation / model building – assessment measures.
3. Risk Model evaluation / model final set up – acceptance measures.
4. Risk Model data (input to model ongoing usage) – quality measurement.
5. Risk Model evaluation / model usage – ongoing monitoring indicators (WP14).

All these evolutions help the bank to better integrate risk measures in the business process, resulting in improved knowledge, pricing and management of the risk taken on by the bank. Linked to this purpose there are several pricing system reviews that most of the banks are undertaking; these reviews aim to better evaluate any credit products during the selling phases and to monitor the real return of each product to eventually alert the credit department for a potential evolution of the contract details. On

the IT side, those issues imply the need for managing real time or near-real time decision systems closely connected to credit risk measurement models; this is a relatively new field of application that will drive integration between credit management and customer management operations in the near future.

Notes

1. SEMMA – sample, explore, modify, model, assess – refers to the core process of conducting data mining. Beginning with a statistically representative sample of the data, SEMMA makes it easy to apply exploratory statistical and visualization techniques, to select and transform the most significant predictive variables, to model the variables to predict outcomes, and to confirm the accuracy of a model.

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12

A New Retail Credit Risk Management Approach to Cope with the Crisis

Francesco Merlin

12.1 Introduction

The economic crisis that started during 2008 clearly shows that many companies, particularly financial institutions, were inadequately prepared to deal with major risks.

Since then, financial firms have struggled to understand how their risk systems failed, ending up with a growing sense that their oversight of risks was superficial and their risk management activities were not well integrated into the company's management system and processes. From this experience a new Enterprise Risk Management (ERM) approach has emerged and started to be applied bit by bit.

As we know, in 2011 a new economic crisis was looming: the European sovereign debt crisis. The impact of this crisis might be felt particularly by retail customers, who lie at the bottom of the "economic food chain".

Therefore, this chapter analyzes in more detail how banks can manage retail credit risk according to this new ERM approach.

12.2 The new ERM paradigm

The new ERM paradigm is made up of five different elements (Figure 12.1).

To better understand the cornerstones of the paradigm, McKinsey recently conducted a survey with 15 international financial institutions that had successfully steered themselves out of the 2008 financial crisis. These firms emerged as winners and clearly seem to have a competitive advantage over the other players in terms of risk management practices

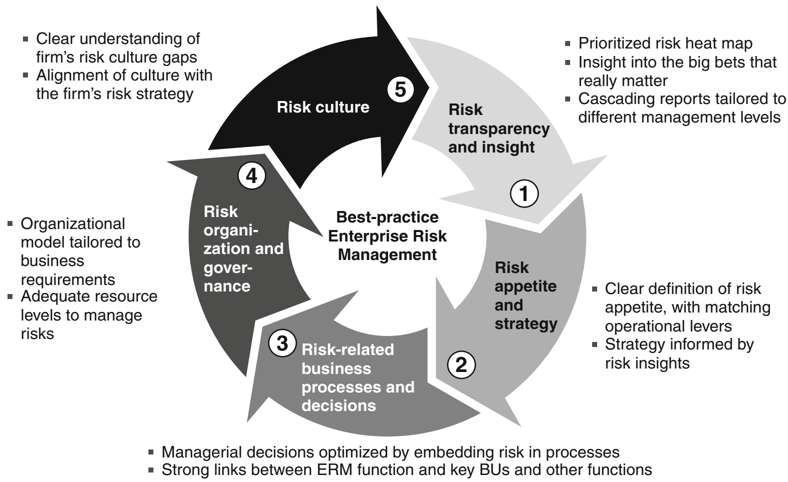

Figure 12.1 Enterprise risk management paradigm
Source: McKinsey (2012).

(Figure 12.2). The best practices in each of the components of the new ERM paradigm are briefly described in Figure 12.2.

Well established risk transparency: On a scale of one (poorly covered) to five (fully covered), best practice scores four, whereas the average score is around two. What elements pushed the score of the best practices up so much?

- Exhaustive risk taxonomy obtained through a fully fledged risk map (heat map), coupled with the ability to identify and prioritize a company's “big bets”.
- Efficient material risk aggregation, providing a holistic view of risk.
- Effective risk infrastructure with a risk reporting system that delivers consistent and insightful information, ready to measure quick changes in risk exposures to promptly address regulatory changes, and to share and challenge risk assumptions.
- Risk foresight capability with early warning key performance indicators (KPIs) for structural risks.

Fully defined risk appetite and strategy: As in the previous case, best practice scores four, and the average score is around two. The competitive advantage results come from:

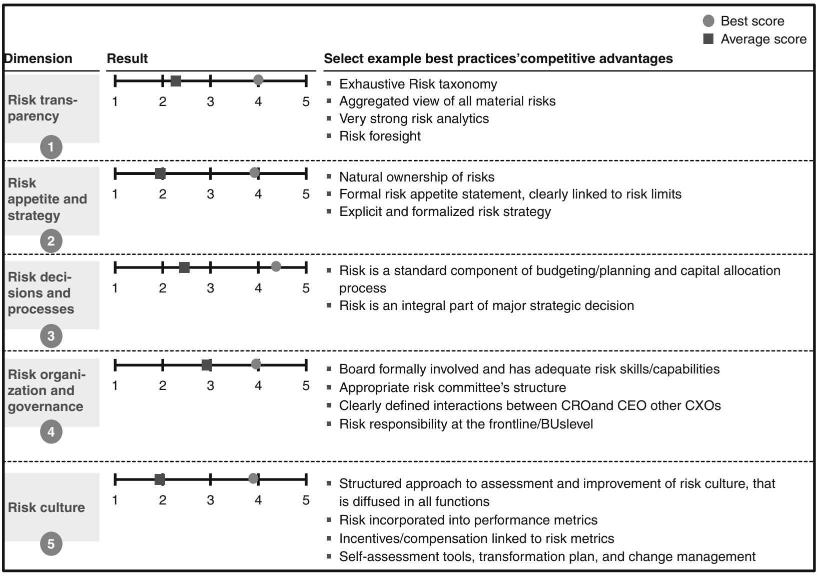

Figure 12.2 Synthesis of best practice survey of risk management
Source: McKinsey (2012).

- Clearly articulated risk appetite, including a formal assessment of a company's risk capacity (the ability to withstand risk when it materializes), and the quantification of how much of that capacity the company should expend (how much risk it should assume), and how much of a cushion should be kept.
- Clearly articulated risk strategy that encompasses which risks make sense for the company to embrace ("natural" ownership), to mitigate (for example, minimizing via managerial actions), to transfer, and to reject (for example which businesses to exit on the basis of risk exposure).
- Full set of risk limits cascading from risk strategy statement.

The "genuine" integration of risk into bank decisions and processes: This time, best practice scores between four and five, and the average score is between two and three. Best practice excels on natively integrated risk frameworks in operations planning and capital management processes, whereas in other players' processes the engagement of risk is solely limited to the "expected" or self-evident risks.

The clear responsibilities and authority of the Chief Risk Officer (CRO): In this area of analysis, best practice scores four, while the average score is three. All forms of best practice seem to share a few golden rules:

- Boards formally involved in risk oversight, with board members directly interacting with management on risk matters and responsible for ensuring that the company has optimized risk management for any risks it might encounter.
- Risk managers sufficiently empowered and able to curb the activities of risk takers and risk traders.
- Articulated risk governance that includes board member and CRO participation.
- Risk ownership naturally owned by risk takers.

Risk culture spread across the company: In this dimension, best practice scores a four with the average two. The main reasons justifying the distinction are:

- Risk management framework: the frame work is integrated in the bank's credit decisions and perceived as a foundational application.
- Risk: included in incentives/compensations and the existence of key risk indicators along with the "regular" KPIs.
- Risk culture: the culture is diffused and engrained in the company's norms and behaviors.

With consideration to retail credit risk management, I now examine how best practice financial institutions integrate the risk mindset into the credit process.

12.3 Risk management in retail credit process

Before delving any further into the topic, it is worth mentioning that even in the middle of the credit crisis the retail credit process is, and will remain, the core source of finance for companies and private individuals. Retail credit will also remain a core driver of bank revenues and profits for the foreseeable future. Despite these elements of continuity, retail credit has changed dramatically due to the crisis; it is expected that continuing demand for bank credit, but a weaker supply, will define and shape the retail credit in the next business cycle. In addition, the ongoing repercussions of the crisis will generate a wave of risk-related loan prolongations, and banks will need to evaluate these requests against a

significant drop in the credit quality of borrowers. On the credit supply side, banks will bear higher costs for balance sheet usage as both capital and funding (especially long-term) will be scarcer and more expensive resources in a stricter regulatory framework.

In this chapter, I carefully examine the different aspects of the new ERM paradigm analyzed in the previous chapter. The chapter looks at the paradigm's impact on the retail credit process and risk-related credit decisions, and how the banks that got the highest ranks in the survey above apply the paradigm.

12.3.1 Origination and underwriting

Once the bank clearly understands its risk appetite, the key challenge is to incorporate that appetite into the bank's risk-taking behavior in the credit process.

To put the risk strategy into operation and take the portfolio on stream, the banks that ranked high in the survey break down overall risk appetite into limits for business units, and even further into limits for specific segments. Within specific segments or business units, the banks developed a risk function and detailed credit standards for application at customer and deal level. This approach allows the bank to define upfront basic parameters for risk decisions. The parameters include industry sector limits, customer rating limits, and loan-to-value limits. By working together to define portfolio limits and credit standards, the banks can reconcile their fundamentally different outlooks on risk, opportunity, and evaluative procedures to reflect the bank's overall policy on risk taking (Figure 12.3).

This topic is also interesting in observing that risk assessment has so far been overly reliant on hindsight (retrospective analysis). Most tools seek to reduce complexity through the statistical analysis of historical data, such as customers' past behaviors or the evaluations of credit bureaus (such as Fair Isaac, Experian and Dun & Bradstreet). But in addition to these historical or retrospective analyses, risk assessment performed by best practice banks also incorporates forward-looking assessments based on a combination of public and confidential documents and the analyst's individual expertise and experience with customers. Risk assessment models, in other words, need to systematically and consistently apply the individual, subjective judgments formed by analysts during their careers.

The introduction of forward-looking parameters most certainly does not make risk assessment any easier, but the combination of hindsight and foresight is proving essential for a thorough understanding of the potential root causes of sources of risk in banks' portfolios.

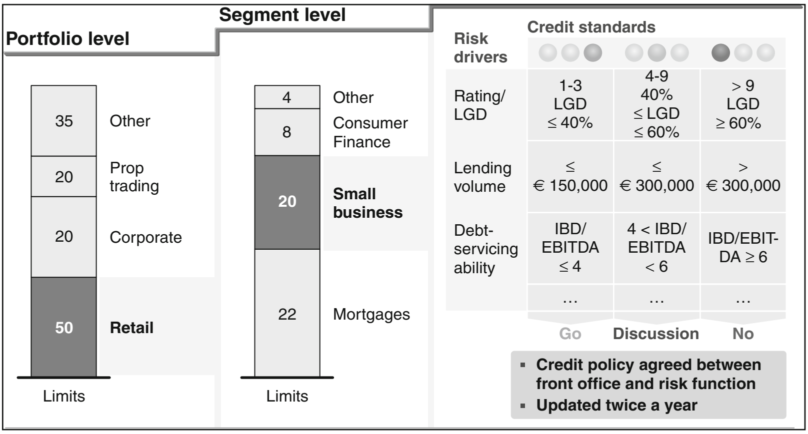

Figure 12.3 Upfront parameter for credit decision
Source: McKinsey (2012).

To strike the right balance between historical and forward-looking analysis, banks have to establish a new pact between rating engines and human insight born of experience. Automated rating processes, for example, highlight factors contributing to risk such as internal indices of a borrower's poor credit management and credit bureau issues. Human decision makers, in contrast, are more effective at focusing on the signs of future risk, forming links and relationships among disparate details, and capturing the nuances that automated analyses are blind to.

Among the alternative approaches for implementing forward-looking risk assessment, two methods are the most successful: the integration of forward-looking quantitative analysis (with statistically established metrics) into the existing rating model; and the running of two separate analyses, one historical, the other prospective.

12.3.2 Strengthen an end-to-end risk mindset in retail credit process

Who is best qualified to lead risk assessment – the market-facing sales group or specialists in an independent risk office? The market-led model has obvious advantages: higher customer satisfaction based on better product capabilities and customization, higher predictability of credit decisions, and full accountability for both risk and revenue for management. But the risk-led model has distinct advantages as well: a higher degree of independence from market expectations, and higher potential

for process differentiation by the type and the complexity of the deal through achieving critical mass in a centralized risk function. The merits of a separate risk function should be revisited in light of the crisis, but ultimately the right balance between market-led and risk-led analysis depends on the strategy of each financial institution – the types of market it serves, its customer communication and marketing strategy (mass market versus high touch), its strategy for future growth, its risk appetite, and so on.

In general, successful banks pursue communication and partnership among the diverse teams and disciplines that steer a loan or credit instrument through the pipeline. To do this successfully, these banks define an end-to-end risk process spanning the front and back offices and consisting of incentives, competency standards, certification, and individual accountability.

The risk function encourages management to de-risk with incentives. Risk indicators such as adherence to risk-cost "corridors", and adherence by the management to the risk function provides a transparent qualitative basis for rewarding cross-functional teams for attaining risk targets.

Also transparency of standards used to define the limit of an individual's authority to make credit decisions are of crucial importance. Thresholds for each level of credit authority (or "competency") are logical, quantitatively measurable, and consistently predictable. Economic capital figures, for example, still seem to be a poor measure for evaluating credit-decision-making competency, because the figures are too volatile and vulnerable to manipulation, and are difficult to communicate. Total exposure, rating, asset type, and risk weights are more stable parameters, and more suitable for the establishment of clear and pragmatic competence levels.

In order to ensure that only qualified people make credit decisions, best practice banks also establish a credit underwriting "driving licence". This is another way, in addition to seniority, to recognize competency. The skill of credit underwriting is part experience, part knowledge, and part talent. Potential decision makers can raise their licence level, for instance, according to the number of decisions they have made in the past, the quality of the portfolio they have underwritten through-the-cycle, and the risk training and capability-building programs they have attended. The licence level can be used both to assign decision-making competencies and to monitor performance and create incentives. To become a senior credit executive would require the highest licence level.

In developing the credit driving licence, coordination among the risk, operations, and IT groups is needed, to simplify procedures for routing origination documents by assigning access rights more dynamically, not simply on the basis of hierarchy, to qualified officers.

The final element of an end-to-end risk mindset is to strengthen individual accountability. Credit committees are common and in some cases appropriate, but they can actually weaken the quality of credit decisions. Evidence shows the danger of socializing responsibility where individuals involved in decisions requiring review and signoff by large numbers at varying levels feel diminished responsibility for their own personal evaluation and judgment. Consequently, credit competence structures, as explained above, aim at assigning a credit decision directly to an appropriately qualified individual or, when necessary, a committee with a limited number of members, to increase the personal accountability of the actual decision makers.

Banks that stay focused on the combined goals of efficiency and effectiveness capture significant value from a best-in-class credit underwriting process. Gains in effectiveness include lower risk cost by as much as 50 percent compared with peers, increases in risk-adjusted returns, and a higher standing with external stakeholders. In these cases, too, efficiency advantages are present; for example in the highest ranked banks approval times are shorter by at least 30 percent.

12.3.3 Credit monitoring and workout

In looking at how the best banks manage credit risk post-origination, two functional areas in credit risk management are the most interesting. The first is monitoring and review, including active exposure management; the second is debt recovery and workout once the normal lending relationship has broken down. In both areas, leading retail banks have moved to more systematic procedures that involve widespread automation and have created excellent operational centers, particularly in debt recovery.

The value of improving credit performance overall is high. Improvements in credit management post-origination typically have a faster impact than those in underwriting, in particular where the flow of new business is modest relative to a crisis period.

The hallmark of excellence in retail credit monitoring and review lies in highly systematic procedures: this means a well structured credit-decision system of codified rules centered on robust automated scoring. This is not to say that there is no room for judgment; but leading banks have pushed the boundaries by making extensive and intelligent use of

automated decision rules in personal and SME credit. Underpinning their ability to do this is the development of behavioral scoring models with high predictive power for the probability of default.

12.3.4 The benefits of systematic procedures in credit workouts

The greatest benefit is reduced credit losses. In the first instance, this benefit arises where the predictive power of the scoring model generates credit decisions that are inherently superior to the judgment of staff experts. Automation can be worthwhile even where the predictive power of behavioral scoring is modest. Where credit exposures are individually small, the cost savings from automated rules are likely to outweigh the impact of the superiority from applying the considered judgment of staff experts in credit decisions. This superiority is much more evident if the model's input data are of good quality in mass-market personal credit and, perhaps, in lending to small businesses. Here, the benefit of a systematic decision process, driven by the rules of a scoring system, arises from the discipline it now imposes. In the past, under the pressure of close customer relationships, lending officers favored lax treatment of potential credit problems. The imposition of new rules avoids this distortion by leading to earlier or more stringent action when customers incur specific problems or suffer from deteriorating macroeconomic circumstances.

Perhaps the most significant reason for reduced credit losses is that monitoring and review can be focused systematically on those customers who pose the greatest risk. A good scoring model provides a granular categorization of customers according to risk (Figure 12.4).

Combining this scoring model with other data, such as size of exposure, a systematic selection process is made to focus staff activity. Best practice, instead of undertaking in-depth credit risk analysis of 30 to 40 percent of the bank's customer base each year, focuses on customers categorized by the scoring model in the two most risky classes, and, as a result, carries out monthly analyses of 2 to 3 percent of the bank's customers. Another option is to move to a two-tier credit renewal system for customers scoring in the lower-risk classes; this system is a fast-track process that is close to automatic renewal but subject to the back-up of biennial review. Then for customers whose scores take them into the higher-risk classes, the review is quarterly instead of annually. Both these systems achieve lower credit losses, but also reduce operating costs by not double-checking low-risk customers, and the resultant cost savings can then be partly used to fund the more intensive review of more risky

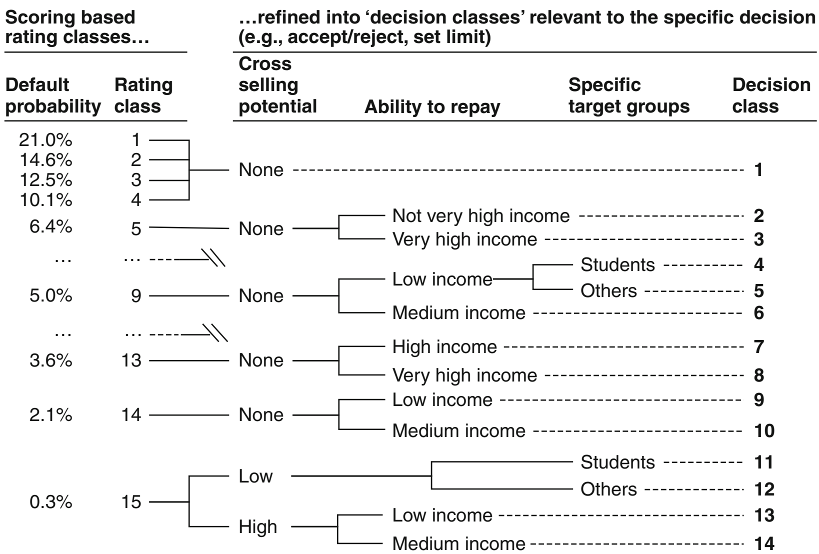

Figure 12.4 Redefinition of scoring-based rating classes
Source: McKinsey (2012).

customers. These cost savings arise from a complex rebalancing of staff activity. But the use of behavioral scoring also results in more straightforward reductions in the running cost of credit operations. The final benefit is that senior management has greater control that almost amounts to the ability to calibrate the intensity of monitoring and exposure management. Senior management can implement changes in credit policy through central changes to the parameters of the rule-driven credit-decision system. For example, changes might entail widening the scope of watch lists by changing the system's selection parameters or by imposing more stringent exposure-reduction targets for customers already on watch lists. Senior management is thus able to calibrate how much it can tighten credit policy and be confident that the new policy will be implemented effectively throughout the bank's network, avoiding the uneven quality often associated with a more decentralized, discretionary approach.

12.3.5 Behavioral scoring

The ability to capture these benefits fully is dependent on a robust behavioral scoring model. Best practice models are distinguished by the range

of relevant input data they use and by the extent to which they successfully incorporate data on customer behavior from the bank's internal information systems.

It is not just the model itself that differentiates best practice. Excellent banks exercise the self-discipline of continuous improvement by tracking performance of the model over time. Some areas of retail credit are particularly amenable to frequent tracking, as the quarterly – or even monthly – cohorts of new business in credit cards or personal loans provide data populations for statistical comparison. These comparisons track changes in the frequency distribution of both scoring outcomes and input variables, such as the occupation of credit card applicants, and test whether these changes are statistically significant. The insights gained can lead to a change in the model or, where they indicate a change in underlying customer behavior, to a change in detailed credit policy (such as raising the minimum monthly repayment for particular segments of credit card borrowers). In small business credit, these insights can lead, for example, to a change in the parameters for selecting customers for exposure-reduction action plans.

12.3.6 Reducing exposures to high-risk customers

A well structured credit-decision system results in a systematic classification of all customers into decision classes. For higher-risk customers, examples of classes include: place on watch list; preparation of an action plan for exposure reduction; and transfer to the debt recovery department. For customers where the normal lending relationship still holds, successful exposure reduction is a critical skill for banks to master, because it is the main route to avoiding or mitigating credit losses post-origination. As with the other functions in the overall credit-decision system, the hallmark of excellence lies in highly systematic procedures in place of an approach reliant on the discretion of the relationship manager. These procedures include: the systematic selection of customers; action plans that define target reduction amounts and timelines; and the monitoring of action plans by an independent specialist unit. The behavioral scoring model –combined if necessary with other data inputs, such as identified vulnerable industry sectors – regularly generates candidates for exposure-reduction action plans, and the credit culture and process ensures that action plans are regularly implemented.

An important element in achieving targets for exposure reduction is to make use of a rich set of exposure-reduction techniques. These can include: reducing limits on revolving credit lines either explicitly or via shadow limits; increasing collateral requirements; introducing or

extending third-party guarantees; restructuring of the credit product; and switching to a lower-risk credit product.

Nevertheless, individual exposure reductions are necessarily limited by contractual or marketing constraints. Hence, in best practice, they are supplemented by portfolio management techniques. With the use of sophisticated risk measurements for portfolios, risk exposure can be reduced even though the cash measure of credit exposure is unchanged or even increased. This can occur, for example, where increased credit exposure in one sector – directly with customers or, more flexibly, through market transactions – provides risk diversification benefits to the aggregate portfolio.

12.3.7 Extracting value from debt recovery

Once the normal lending relationship has broken down, the primary objective becomes the maximization of debt recovery after allowing for costs of pursuit and collection plus the interest generated by the delay. In some cases, the most appropriate route is to minimize costs either by not pursuing the debt or by initiating insolvency or bankruptcy procedures. But best practice banks apply other strategies which prove to be more productive.

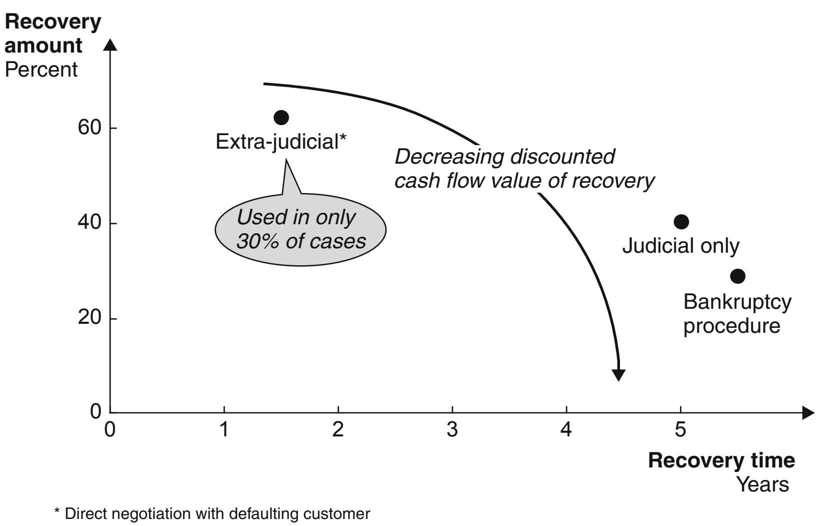

Figure 12.5 Comparison of debt recovery strategies in Italian banking
Source: McKinsey (2012).

These strategies require skills in extrajudicial negotiation, in legal pursuit, and in workouts – ranging from relatively simple debt restructuring to complex "intensive care". Intensive care is primarily relevant for significant corporate customers. It can involve complex debt restructuring; include the appointment of specialist turnaround managers; and, on rare occasions, entail new funds. Where successful, the customer is nursed back to a normal lending relationship. Leading banks have recognized the value of these alternative strategies and have reorganized to create and sustain the necessary skills. The features of a best practice organization in debt recovery can be illustrated by the approach adopted by one of the retail banks in the analyzed sample. There is a unit specializing in recovery and reporting direct to the CEO. That report provides the unit with significant bargaining power in dealing with the bank's commercial business units (for example, determining when a nonperforming loan becomes the responsibility of the recovery unit and setting the internal price at which it is transferred). This power results in earlier transfers of nonperforming loans to the recovery unit, increasing the probability of successful recovery, and encouraging the commercial business units to be more vigilant in identifying potential problem loans. Within the unit, activity is divided into three distinct departments: corporate recovery, retail recovery, and insolvency or bankruptcy proceedings. This structure reflects the different skills and approaches suited to each segment. Specifically, in retail recovery, the emphasis is on containing the cost of pursuit and collection through extensive use of remote pursuit by phone or mail – already a common strategy at non-branch consumer credit banks. Retail recovery is also supported by significant systems investment, particularly in an IT-based workflow management system. Amongst other functions, the system helps efficient selection and control of individual debt recovery strategies up a ladder of escalating actions (remote pursuit by phone or mail, visits, then court action) that comprises a quantitative assessment as to whether the expected benefits outweigh the costs of moving up the ladder. The recovery unit operates as a profit centre mainly with internal income from the commercial business units, and the emphasis on financial performance is further enhanced by very strong individual performance incentives. Supplementing its core staff, the unit operates a network of external recovery officers that work to common standards supported by bank training and IT, but are not salaried employees of the bank. They are remunerated by a scale of fees linked to the amount recovered, and their performance in terms of speed of recovery is rewarded through the size and mix of the portfolio of loans allocated to them.

In times of credit downturns, excellence in these areas will be a crucial differentiator of banks' financial performance. The key to achieving such excellence lies in organizational focus and systematic procedures, tailored to the requirements of different segments.

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